

Durham E-Theses

The application of rule-based knowledge to load forecasting of electrical power systems

Chang-mei Li

How to cite:

Li, Chang-mei (1990) The application of rule-based knowledge to load forecasting of electrical power systems. Doctoral thesis, Durham University.

Use policy

The full-text may be used and/or reproduced, and given to third parties in any format or medium, without prior permission or charge, for personal research or study, educational, or not-for-profit purposes provided that:

- a full bibliographic reference is made to the original source
- a <https://etheses.durham.ac.uk/id/eprint/6295/> is made to the metadata record in Durham E-Theses
- the full-text is not changed in any way

The full-text must not be sold in any format or medium without the formal permission of the copyright holders.

Please consult the [full Durham E-Theses policy](#) for further details.

ABSTRACT

The thesis describes short-term load forecasting by an expert system approach based on knowledge engineering. Conventionally, short-term load prediction is based on mathematical models which either extract the mathematical properties in the time series of load data, or present the static causal relationships between the load demand and its effective factors. The conventional methods can predict the electrical demand under normal situations, but not for special events. The thesis proposes a new approach to estimate the loads for special events, such as time change-overs, public holidays, which is mainly based on knowledge about the system load. Based on the ARIMA model, modifications have been made to predict weekend loads, which take the weather effects into consideration. The thesis also proposes a method to disaggregate the overall load into its components in order to study the relationships between the components and the causal variables. The time change-over (from Greenwich Mean Time to British Summer Time and vice versa) effects can be considered by separately estimating the lighting load and the rest load. The thesis investigates the holiday load characteristics and presents different estimation methods for different public holidays ranging from normal Monday Bank Holidays to Christmas Day holiday periods. Knowledge about the load is represented in production rules. The proposed estimation methods are written in POP-11 which can be interfaced with FORTRAN in which the ARIMA model is programmed for the prediction of the load under normal situations.

The Application of Rule-based Knowledge
to
Load Forecasting of Electrical Power Systems

by

Chang-mei Li

The copyright of this thesis rests with the author.
No quotation from it should be published without
his prior written consent and information derived
from it should be acknowledged.

A thesis submitted for the degree of

Doctor of Philosophy

in Faculty of Science

University of Durham

October 1990



14 NOV 1991

ACKNOWLEDGEMENTS

I sincerely acknowledge the financial support of the British Council and the Chinese Government which makes the project possible. I would like to thank Professor M.J.H. Sterling for his supervision and guidance throughout the project. I would like to express my gratitude to all the OCEPS members, especially Dr. M.R. Irving and J.O. Gann for their advice and guidance, and also the technical staff of the School of Engineering and Applied Science, University of Durham.

Finally I would like to express my gratefulness to my mother and brothers for their encouragement during my period of study in England.

CONTENTS

	Page
Abstract	
Title	
Acknowledgements	i
Contents	ii
List of figures	vi
List of tables	x
Statement of copyright	xiii
Declaration	xiv
Chapter One INTRODUCTION	
1.1 Introduction to electrical power systems	1
1.2 Control of electrical power systems	3
1.3 Presentation of the thesis	10
Chapter Two CONVENTIONAL APPROACHES TO SHORT-TERM LOAD FORECASTING	
2.1 Introduction	13
2.2 Characteristics of electrical load	14
2.2.1 Intrinsic properties	14
2.2.2 Influence of weather conditions on load	20
2.2.3 Public holiday effects	22
2.2.4 Time change-over effects	22
2.2.5 Other special event effects	25
2.3 Data requirements	25
2.4 Design features	26
2.5 Conventional approaches	28
2.5.1 Linear regression method	29
2.5.2 Spectral expansion method	33
2.5.3 General exponential smoothing method	37
2.5.4 Harmonic decomposition method	41
2.5.5 Pattern recognition method	43
2.5.6 Autoregressive Integrated Moving Averages (ARIMA)	45
2.5.7 Unusual situations	51
2.5.7.1 TV pick-ups	51

2.5.7.2	Public holidays	52
2.6	Summary	54
Chapter Three ARTIFICIAL INTELLIGENCE TECHNIQUES		
3.1	Introduction	56
3.2	Introduction to expert systems	57
3.2.1	Types of expert systems	57
3.2.2	Components of expert systems	60
3.3	Related AI techniques	61
3.3.1	Knowledge acquisition	61
3.3.2	Knowledge representation	63
3.3.2.1	Knowledge representation using rules	63
3.3.2.2	Knowledge representation using semantic nets	65
3.3.2.3	Knowledge representation using frames	66
3.3.3	Inference mechanism	66
3.3.4	Man-machine interface	69
3.4	Applications of expert systems	69
3.5	Expert systems for short-term load forecasting	83
3.6	Summary	85
Chapter Four AN APPLICATION OF AN EXPERT SYSTEM TO SHORT-TERM LOAD FORECASTING		
4.1	Introduction	87
4.2	The necessity of decomposing the overall load into its components	88
4.3	Classification of electrical load	90
4.3.1	Representation of the components	94
4.3.2	Expression of components using the basic curves	95
4.4	Summation of the components into the overall load	101
4.5	Objective functions	102
4.6	Fitting of the components	103
4.6.1	Estimation of weight for each component	103
4.6.2	Curve modification method	104
4.6.2.1	Changing normal curves	104
4.6.2.2	Changing pos-neg curves	105
4.6.3	Sequence of modifications	108

4.6.3.1	Order of changing components	108
4.6.3.2	Order of changing basic curves	109
4.7	Results	109
4.8	Summary	115
Chapter Five LOAD PREDICTION OVER TIME CHANGE-OVERS		
5.1	Introduction	116
5.2	Load characteristics around time change-overs	117
5.2.1	From GMT to BST	120
5.2.2	From BST to GMT	120
5.3	Prediction by ARIMA	121
5.4	Prediction by adoption of relative gaps	133
5.5	Expert system approach	137
5.5.1	From GMT to BST	139
5.5.2	From BST to GMT	140
5.6	Knowledge about lighting-up loads	155
5.7	Assessment of different approaches	156
5.8	Discussion and conclusion	161
Chapter Six LOAD FORECASTING INCLUDING HOLIDAY EFFECTS		
6.1	Introduction	163
6.2	Characteristics of load over special periods	164
6.3	Prediction by factoring the results of ARIMA	171
6.4	Prediction by referring to preceding weekends	175
6.4.1	Predicting holidays by past data	175
6.4.2	Including weather effects on holidays	182
6.4.3	Load prediction for Good Friday	184
6.5	Predicting loads of special holidays	187
6.6	Predicting loads over periods between Christmas day and New Year's day	193
6.7	Eliminating holiday effects on normal period prediction	196
6.8	Knowledge about special events	202
6.9	Examples of programmes in POP-11	203
6.10	Discussion and conclusion	207

Chapter Seven	LOAD FORECASTING INCLUDING WEATHER EFFECTS	
7.1	Introduction	209
7.2	Weather variables to be included in the models	211
7.3	Data for prediction	212
7.4	Interface between FORTRAN and POP-11	214
7.5	Prediction by averaging predicted load with actual load . . .	216
7.6	Prediction by error threshold detection	223
7.7	Prediction by employing actual weather information	237
7.8	Discussion and conclusion	246
Chapter Eight	CONCLUSION	
8.1	Conclusion	248
8.2	Future work related with load prediction	251
	REFERENCES AND BIBLIOGRAPHY	253
Appendix 1	CALCULATION OF AUTOCORRELATION FUNCTION	280
Appendix 2	LOAD PREDICTION PACKAGE	282
Appendix 3	SOME POP-11 PROGRAMMES	288

LIST OF FIGURES

Page

Chapter 1

Figure 1.1 Overview of Major Functional Elements of Power System Control 5

Chapter 2

Figure 2.1 Typical Summer Week Load Profile 15

Figure 2.2 Typical Winter Week Load Profile 16

Figure 2.3 Typical Daily Load Profiles in Summer and Winter 17

Figure 2.4 Effect of Weather Conditions on Electrical Demand 19

Figure 2.5 Effect of Holidays on Electrical Demand 21

Figure 2.6 Effect of Time Change-over (BST – GMT) 23

Figure 2.7 Effect of Time Change-over (GMT – BST) 24

Figure 2.8 Structure of ARIMA 49

Chapter 3

Figure 3.1 Components of Expert Systems 62

Figure 3.2 Execution of Rules 62

Figure 3.3 Representation by Semantic Nets 67

Figure 3.4 Frame-based Representation 68

Chapter 4

Figure 4.1 Typical Load Shape for Industrial Demand 91

Figure 4.2 Typical Load Shape for Commercial Demand 92

Figure 4.3 Typical Load Shape for Domestic Demand 93

Figure 4.4 Five Basic Curves 96

Figure 4.5 Modification of Curves 106

Figure 4.6 Disaggregated Residuals for Winter Weekday (01/02/1984) 111

Figure 4.7 Actual Load and Summation of Components
for Winter Weekday (01/02/1984) 112

Figure 4.8	Disaggregated Residuals for Summer Weekday (06/06/1984)	113
Figure 4.9	Actual Load and Summation of Components for Summer Weekday (06/06/1984)	114
Chapter 5		
Figure 5.1	Effects of Time Change-overs on Load (GMT - BST)	118
Figure 5.2	Effects of Time Change-overs on Load (BST - GMT)	119
Figure 5.3	Prediction of GMT/BST Effects for Monday by ARIMA	123
Figure 5.4	Prediction of GMT/BST Effects for Tuesday by ARIMA	124
Figure 5.5	Prediction of GMT/BST Effects for Wednesday by ARIMA	125
Figure 5.6	Prediction of GMT/BST Effects for Thursday by ARIMA	126
Figure 5.7	Prediction of GMT/BST Effects for Friday by ARIMA	127
Figure 5.8	Prediction of BST/GMT Effects for Monday by ARIMA	128
Figure 5.9	Prediction of BST/GMT Effects for Tuesday by ARIMA	129
Figure 5.10	Prediction of BST/GMT Effects for Wednesday by ARIMA	130
Figure 5.11	Prediction of BST/GMT Effects for Thursday by ARIMA	131
Figure 5.12	Prediction of BST/GMT Effects for Friday by ARIMA	132
Figure 5.13	Prediction of GMT/BST Effects by R.G.1 and R.G.2	135
Figure 5.14	Prediction of BST/GMT Effects by R.G.1 and R.G.2	136
Figure 5.15	The Evening Lighting Load Profile	138
Figure 5.16	Prediction of GMT/BST Effects for Monday by ES	141
Figure 5.17	Prediction of GMT/BST Effects for Tuesday by ES	142
Figure 5.18	Prediction of GMT/BST Effects for Wednesday by ES	143
Figure 5.19	Prediction of GMT/BST Effects for Thursday by ES	144
Figure 5.20	Prediction of GMT/BST Effects for Friday by ES	145
Figure 5.21	Prediction of BST/GMT Effects for Monday by ES	146
Figure 5.22	Prediction of BST/GMT Effects for Tuesday by ES	147
Figure 5.23	Prediction of BST/GMT Effects for Wednesday by ES	148
Figure 5.24	Prediction of BST/GMT Effects for Thursday by ES	149
Figure 5.25	Prediction of BST/GMT Effects for Friday by ES	150
Figure 5.26	RMS Errors of Different Approaches (GMT/BST)	151
Figure 5.27	Max. Errors of Different Approaches (BST/GMT)	152
Figure 5.28	RMS Errors of Different Approaches (BST/GMT)	153
Figure 5.29	Max. Errors of Different Approaches (BST/GMT)	154

Figure 5.30	Overall Errors by Different Approaches (GMT/BST)	. . . 159
Figure 5.31	Overall Errors by Different Approaches (BST/GMT)	. . . 160

Chapter 6

Figure 6.1	Effects of Public Holidays 166
Figure 6.2	Load Behaviour on Weekends and Monday Bank Holiday	. 167
Figure 6.3	Loads of Different Public Holidays 168
Figure 6.4	Load Behaviour Between Christmas Day and New Year's Day 169
Figure 6.5	Similarity of Load for Same Public Holiday Each Year	. . 170
Figure 6.6	Load Prediction for May-day (1985) by R.G.1 and R.G.2	. 174
Figure 6.7	Results for Summer Bank Holiday (1985) 178
Figure 6.8	R.M.S. Errors of Different Approaches for Holidays	. . . 180
Figure 6.9	Maximum Errors of Different Approaches for Holidays	. . 181
Figure 6.10	Prediction with and Without Weather Consideration	. . 185
Figure 6.11	Prediction of Loads for Good Friday 186
Figure 6.12	Prediction of Loads for Christmas Day 190
Figure 6.13	Prediction of Loads for Boxing Day 191
Figure 6.14	Prediction of Loads for New Year's Day 192
Figure 6.15	Prediction of Loads for 27/12/1983 (Tuesday) 194
Figure 6.16	Prediction of Loads for 30/12/1984 (Sunday) 195
Figure 6.17	Effects of Holidays on Neighbouring Days and Weeks	. . 198
Figure 6.18	Predicting the Holiday Period Load by ARIMA 199
Figure 6.19	Comparison of Two Approaches 200

Chapter 7

Figure 7.1	Comparison of ARIMA with Load Averaging of Winter Weekends 218
Figure 7.2	Comparison of ARIMA with Load Averaging of Summer Saturdays 220
Figure 7.3	Comparison of ARIMA with Load Averaging of Summer Sundays 222

Figure 7.4	Comparison of ARIMA with Error-threshold-detection of Winter Weekends	225
Figure 7.5	Comparison of ARIMA with Error-threshold-detection of Summer Saturdays	227
Figure 7.6	Comparison of ARIMA with Error-threshold-detection of Summer Sundays	229
Figure 7.7	Comparison of ARIMA with Combined Prediction of Winter Weekends	232
Figure 7.8	Comparison of ARIMA with Combined Prediction of Summer Saturdays	234
Figure 7.9	Comparison of ARIMA with Combined Prediction of Summer Sundays	236
Figure 7.10	Comparison of ARIMA with Weather Consideration of Winter Weekends	241
Figure 7.11	Comparison of ARIMA with Weather Consideration of Summer Saturdays	243
Figure 7.12	Comparison of ARIMA with Weather Consideration of Summer Sundays	245

LIST OF TABLES

	Page
 Chapter 2	
Table 2.1	Autocorrelation Function with Time Lag 18
Table 2.2	Weather Data and Load Data 20
Table 2.3	Weather Weight Variation with Monthly Temperature 29
Table 2.4	Weather Weight Variation with Cloud Cover 30
 Chapter 3	
Table 3.1	Generic Categories of Knowledge Engineering 60
Table 3.2	Current KE Application 70
 Chapter 4	
Table 4.1	Total Consumption of Industrial and Commercial Customers with Demand of 1 MW and over 89
Table 4.2	Residuals of Disaggregated Load 110
 Chapter 5	
Table 5.1	Load Prediction Around Time Change-over by ARIMA (GMT - BST) 121
Table 5.2	Load Prediction Around Time Change-over by ARIMA (BST - GMT) 121
Table 5.3	Results of Prediction by Relative Gaps (GMT - BST) . . . 134
Table 5.4	Results of Prediction by Relative Gaps (BST - GMT) . . . 134
Table 5.5	Prediction by Expert System (GMT - BST) 140
Table 5.6	Prediction by Expert System (BST - GMT) 155
Table 5.7	Prediction by Different Approaches (GMT - BST) 157
Table 5.8	Prediction by Different Approaches (BST - GMT) 158

Chapter 6

Table 6.1	Results of Predicting Load for Fixed Bank Holidays by R.G.1 and R.G.2 (1985)	173
Table 6.2	Comparison of Prediction by Different Approaches	179
Table 6.3	Results of Prediction with Weather Considered for Public Holidays (1985)	183
Table 6.4	Results of Prediction for Good Friday	187
Table 6.5	Daily Holiday Correction Factors for Special Holidays	188
Table 6.6	Results of Prediction for Christmas Day	188
Table 6.7	Results of Prediction for Boxing Day	189
Table 6.8	Results of Prediction for New Year's Day	189
Table 6.9	Results of Predicting Load for Periods Between Christmas Day and New Year's Day (1983)	196
Table 6.10	Results of Predicting Load for Periods Between Christmas Day and New Year's Day (1984)	196
Table 6.11	Effects of Holidays of ARIMA Method on Neighbouring Days and Weeks	201

Chapter 7

Table 7.1	Comparison of ARIMA with Load Averaging of Winter Saturdays	217
Table 7.2	Comparison of ARIMA with Load Averaging of Winter Sundays	217
Table 7.3	Comparison of ARIMA with Load Averaging of Summer Saturdays	219
Table 7.4	Comparison of ARIMA with Load Averaging of Summer Sundays	221
Table 7.5	Comparison of ARIMA with Error-threshold-detection of Winter Saturdays	224
Table 7.6	Comparison of ARIMA with Error-threshold-detection of Winter Sundays	224

Table 7.7	Comparison of ARIMA with Error-threshold-detection of Summer Saturdays	226
Table 7.8	Comparison of ARIMA with Error-threshold-detection of Summer Sundays	228
Table 7.9	Comparison of ARIMA with Combined Prediction of Winter Saturdays	231
Table 7.10	Comparison of ARIMA with Combined Prediction of Summer Sundays	231
Table 7.11	Comparison of ARIMA with Combined Prediction of Summer Saturdays	233
Table 7.12	Comparison of ARIMA with Combined Prediction of Summer Sundays	235
Table 7.13	Comparison of ARIMA with Weather Consideration of Winter Saturdays	240
Table 7.14	Comparison of ARIMA with Weather Consideration of Winter Sundays	240
Table 7.15	Comparison of ARIMA with Weather Consideration of Summer Saturdays	242
Table 7.16	Comparison of ARIMA with Weather Consideration of Summer Sundays	244

COPYRIGHT

The copyright of the thesis rests with the author. No quotation from it should be published without her prior written consent and information derived from it should be acknowledged.

DECLARATION

None of the material contained in the thesis has been previously submitted by me for a degree in this or any other university and the work represents my own original contribution.

CHAPTER 1

INTRODUCTION

1.1 Introduction to electrical power systems

An electrical power system is defined as a network of interconnected components designed to convert non-electrical energy continuously into the electrical form; to transmit the electrical energy over potentially great distances; to transform the electrical energy into a specific form subject to close tolerances; and to convert the electrical energy into a usable form. To be practical, it must be secure, reliable and economical. The process of supplying the consumer with electricity can be divided into three distinct functions, namely generation, transmission and distribution.

Generation:

Electricity generation involves the conversion of a primary energy source into electrical energy. The most common primary energy sources are fossil fuels, i.e., coal and oil. In the Central Electricity Generating Board (CEGB) system this accounts for approximately 85 per cent of the requirements. The remainder is generated by nuclear (approximately 12.5 per cent), gas turbine, diesel and hydro-electric generating equipment. Fossil and nuclear fuels are used to produce heat which is converted into the rotational energy of generators by boiling water to create high pressure steam which is then passed through a turbine. Similarly, gas turbine generators pass hot burning gases through a turbine while hydro-electric power stations pass water through a turbine under pressure obtained by storing water in a reservoir situated above the turbine. Diesel generators differ from the others in that a conventional internal combustion engine is used to convert the diesel fuel into rotational energy. The rotational energy



generated by utilising a primary energy source is transformed into electricity in a sinusoidal waveform by a generator which exploits the electro-magnetic interactions between a magnetic field and a moving conductor. Modern steam turbine generators usually have a terminal voltage of 23.5 KV and a power output of up to 660 MW. A large power station may have as many as six generators. The CEGB system has approximately 90 large and efficient power stations with a total generating capacity in excess of 52 GW.

The location of a power station is governed by two major factors: easy transport of fuel to the power station and location of a plentiful supply of water for cooling purpose. Thus power stations are usually located on a coast or a large river and in the case of coal-fired stations, near to a coal field; whilst the large consumers are often located far away from the stations.

Large thermal generators whether they be fossil fuel or nuclear units, are usually the most economical to run, and thus, they are usually run continuously at a fairly steady output level. As would be expected, the output of a large generating unit can not change quickly and it may take several hours to synchronise such a generator to the network from a cold start. Gas turbine generators are, however, expensive to run, but they are fast and can be synchronised to the system within a matter of minutes. So they are used to meet sharp increases in the load in the system or during emergency conditions. Pumped storage hydro-electric generating schemes are an alternative method of meeting the sharp increases in the load curve. Pumped storage units are operated as follows. During the period of low demand, electricity is used to pump water from a lower reservoir to an upper reservoir. This utilisation of the power enables some of the large thermal units to remain synchronised with the system during the slack periods. When the load increases the water stored in the upper reservoir is returned to drive a hydro-electric generator.

Electrical energy is not a kind of energy that can be stored as other resources. The balance between the load demand and the power generated must be held all the time. If this balance fails, then the frequency will change accordingly. The frequency variation of the power system can be used as an

indicator of the imbalance. If the system frequency falls, then more energy should be supplied to generators in order to produce more electrical energy to balance with the loads.

Transmission:

Usually large power plants are located on a coast or near a coal field, whereas the consumer regions are far from the power stations. Consequently, the role of transmission sections of a power system is to transmit the power from the power station to the load centres of the network by high voltage overhead transmission lines or underground cables. In order to reduce transmission losses, the transmission network is operated at high voltages. The transmission network of the CEGB is operated at 275 KV (grid) and 400 KV (supergrid).

From the viewpoint of security, the transmission network must be designed in such a way that the loss of a few lines does not completely disable the system.

Distribution:

The distribution networks are usually supplied by several bulk supply points from the transmission network. The voltage level is transformed from a high transmission voltage to a lower level at which the power can be consumed by the users. The domestic user is supplied by a single phase of the distribution network, usually with a voltage of 240 V above the ground potential, while industrial consumers may be supplied with a three-phase distribution network at a voltage level which is suitable for their requirements. The distribution network in England and Wales is maintained by 12 distribution companies (formerly the area boards).

1.2 Control of electrical power systems

In order to make the generation, transmission and distribution systems work well together, it is necessary to have a control function to co-ordinate the

whole power system operation. Power system control is required to maintain a continuous balance between electrical generation and a varying load demand, i.e., a stable system frequency, whilst voltage levels and security are maintained. Another desirable objective of the power system control is to minimise the cost of operation. The control of generating units is a complex problem which needs to consider the following criteria: the likely load both in the near future (e.g., in the next 30 minutes) and the more distant future (e.g., in the next 4-6 hours), the time for a generator to be synchronised if it is not already synchronised, and the rate of change of the output of a generator once it is synchronised.

The control of a power system is a hierarchical process which commences with the prediction of the load demand at a control centre and ends with closed loop controllers which regulate the primary energy source supplied to the generators in response to variations in the desired and actual values of frequency and output power (see Figure 1.1). The hierarchical levels in the control sequence include the long term planning of which generators need to be synchronised (unit commitment) based on the long term load forecasting, the short term adjustment of the desired levels of generation (economic dispatch) based on the short term load forecasting, the desired operating frequency, and finally the continual adjustment of the generator regulators by the closed loop controllers. Therefore, the overall operation and control scheme needs the following procedures:

Load prediction:

Electrical power system operation starts from short term load prediction the objective of which is to predict the system load in the near future (several hours to several days ahead) so that prior warning of output requirements may be given to power stations.

The quality of control of a power system, and the economy of operation, are highly sensitive to load forecasting error. In consequence, it is expedient to

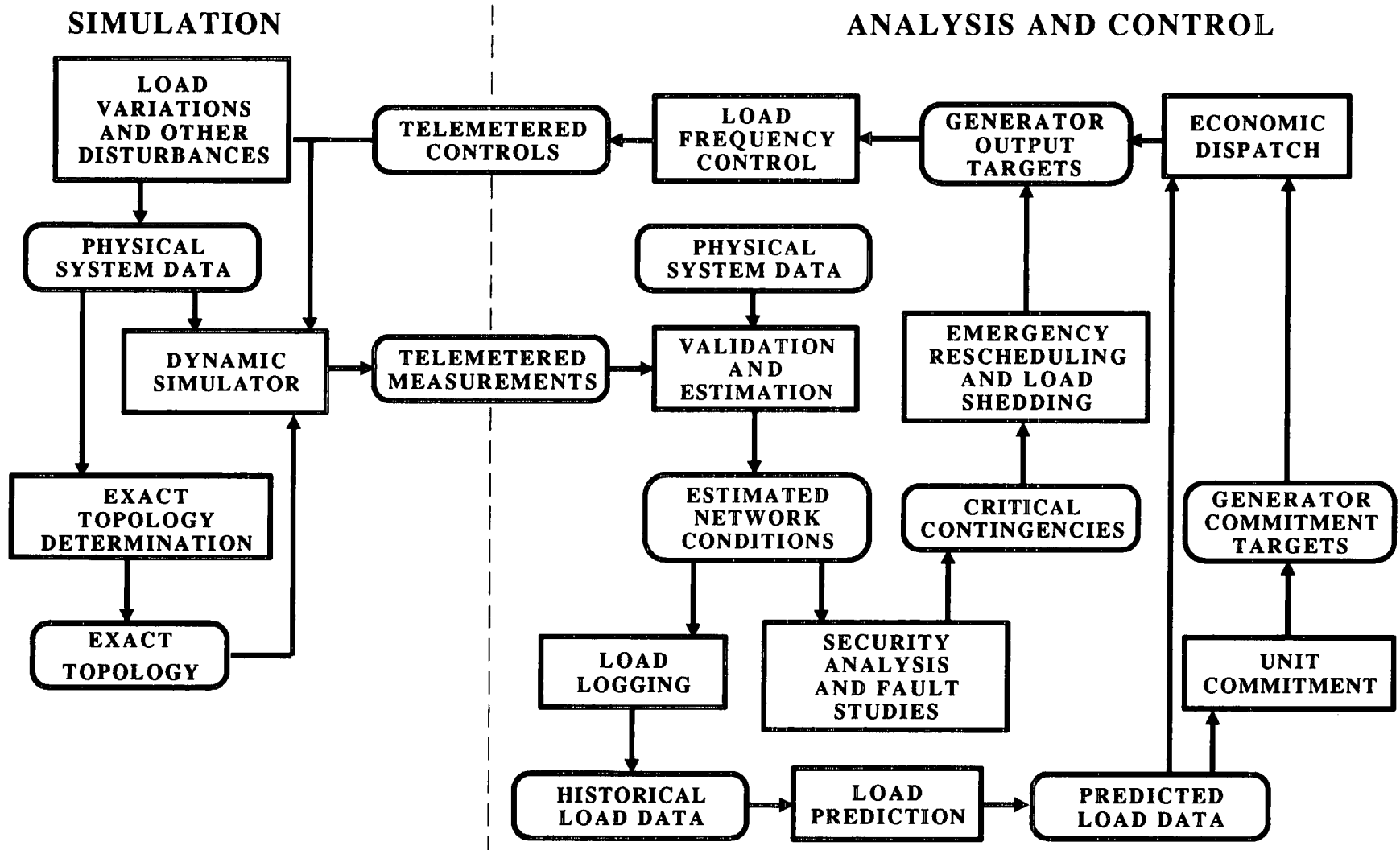


Figure 1.1 Operational Control of Electrical Power Systems
Overview of Major Functional Elements

develop forecasting techniques to the stage where the magnitudes of the errors have attained irreducible proportions.

Off-line weather-dependent forecasting models are essential for lead times of more than a few hours. There are several reasons for this. In the first place, the on-line use of weather data for a real-time forecasting system requires either a reliable weather metering system or the regular external input of weather variable forecasts from a meteorological service. Secondly, it has been suggested that univariate adaptive procedures will implicitly be tracking most weather-induced changes over the short-term and thus little extra prediction accuracy would be gained from constructing a more elaborate multivariate weather dependent model.

With the development of powerful computers, many problems which could only be solved by experienced human operators or experts in the past, can now be solved by computers. The programs, referred to as "expert systems", can manipulate knowledge in the domain and perform reasoning like a human being. Expert systems have been successfully applied to many fields, as well as in power systems.

This thesis will focus on electrical load prediction by combining the mathematical analytical tools with the human expertise.

Plant ordering:

After the electrical demand for the next 24 hours has been forecast, generating units can be ordered in order that the peak demand can be safely met. Since the demand varies along time and the load near its peak value lasts only several hours each day, it may be economic to shut down some units during the off-peak periods. Start-up and shut-down of units can be ordered in order to obtain the optimal combination of units which can meet the load demand. Thus, the problem of plant ordering can be represented as a coarse running cost optimisation so that the system load and spinning reserve are met with the consideration of some constraints. The constraints include the

start-up and shut-down time for each unit. Of course, cheaper units should be scheduled before less efficient units. During the off-peak period, the inefficient units may be shut down in order to save operational cost. But later, prior to the next peak load, they will have to be restarted. So, the saving obtained by shutting down a unit must be compared with the start-up cost of the unit so that overall economic operation can be obtained. Therefore, the following factors have to be considered in plant ordering:

1. The shape of consumer demand;
2. The fuel cost curve of each unit;
3. Reserve requirements;
4. Unit shut-down time and start-up time constraints;
5. Start-up cost as a function of shut-down time;
6. Capacity of units (maximum and minimum);

If there are also hydro generation units in the system, then co-ordination of thermal units and the hydro generators must be considered. Since hydro generation is much cheaper to operate than the thermal generation, optimal savings may be expected if the hydro generation is scheduled during peak load time. Hydro unit scheduling is to determine the water release from each reservoir and through each power station so as to optimise the total benefit of the hydro-generated energy. Therefore, hydro scheduling and thermal scheduling should be co-ordinated so that the overall cost can be minimised.

Economic dispatch:

Plant ordering only determines the on and off status of each unit. The output of each unit at specific times is determined by economic dispatch so that the varying load can be met and the production cost is minimised. Economic dispatch is therefore required to minimise the overall operation costs subject to a set of constraints, such as the maximum and minimum outputs of each unit.

Load frequency control:

As stated earlier, system frequency variation can be used as an indicator of imbalance between the load demand and the electricity generation. In a complex inter-connected power system, many separate companies (for example, in U.S.A.) jointly provide a secure and economic power supply to widely distributed consumers via tie-lines. Load frequency control is needed to maintain the system frequency at a desired level by adjusting the set point of the area requirement which includes regulating the frequency variation from nominal, and the net deviation of the line power flows from their scheduled values.

Voltage control:

It has been explained that the consumer centre is usually not located near the generation centre, so it is necessary to transmit a great amount of energy by transmission networks from power stations to consumer centres. As heavy loads flow through transmission networks, voltage drops are inevitable at the consumer location. It is sometimes necessary to install shunt capacitors in order to maintain the voltage at a nominal level. In another sense, the reactive power produced by generators may not be enough for the requirement of consumers. The shunt capacitors are required to produce some reactive power to compensate for that lost in transmission lines and to meet the consumers' requirements. Conversely, when the load is light, the line capacitance may raise the voltage level beyond the acceptable limits. In this case, inductors are used to absorb the surplus reactive power. Consequently, the voltage level has to be controlled within the desired limits by appropriate means.

State estimation:

In order to operate and control a power system, up to date and accurate information about the state of the entire network is required. Most of the system variables are telemetered. Due to instrumentation and telemetry noise, inaccurate network parameters and delayed measurements may arise. In order to supply the operator with accurate information, raw measurements have to be

processed. The measurements are then validated to remove those errors, and values are calculated for all the unmeasured points. For example, the historical load data for load prediction are from the validation and estimation of teleme-tered measurements of demands. State estimation also performs calculations to advise the operator if an emergency condition would arise from the loss of any single piece of equipment.

Security analysis and fault studies:

In an operational environment, security assessment consists of predicting the vulnerability of the system to some unforeseen, but possible disturbances on a real-time basis. Because of maintenance requirements, forced outages, and changing load patterns, actual operating conditions are continuously changing, and so are the levels of system security. When some disturbances happen to the system, a redistribution of power flows and voltages may be expected, this can result in an overloaded line, or an overvoltage condition. The system may tolerate such limit violations for a short period of time. Corrective action should be taken in such a period so that the system can recover to a normal condition. Analysis tools required for security assessment are based on load flow studies to find out the limit violations.

The normal operation of a power system may be disturbed or disrupted by faults. These can be single line-to-ground, line-to-line, double line-to-ground, three-phase to ground, one line open, two lines open, or combinations of them. Faults can damage the equipment, cause danger to human bodies, and jeopardise the operation of other parts of the system. So, in the event of any faults, investigation must be made to find out the types, locations and reasons for the faults in order to find the appropriate solutions to clear the faults and restore the faulty elements or areas.

Emergency rescheduling and load shedding:

During emergency conditions, generation capacity may not be sufficient to meet system loads. It is important to rapidly reschedule generation and

allocate the degree of load shedding. Under emergency conditions, economic operation has a lower priority than the minimisation of load shedding. Generally, artificial costs are assigned to each load supply point, and a priority order of load shedding is drawn up.

1.3 Presentation of the thesis

The thesis presents a study of short term load forecasting by using knowledge based expert systems and the univariate auto-regressive integrated moving average (ARIMA) method. The results throughout the thesis are obtained by testing the methods against the CEGB system loads. The thesis is divided into a total of eight chapters. The following paragraphs outline the contents of the remaining chapters.

The second chapter presents a review of previously published methods of short term load forecasting. The first section of chapter 2 gives an introduction to system load, followed by section 2 which describes the characteristics of system load. In this section, the characteristics of system load variations with time and with the effective factors are given, as well as the influences of such special events on system load as public holidays and time change-overs both from Greenwich Mean Time to British Summer Time and vice versa. Sections 3 and 4 in this chapter describe data requirements for load prediction and the design features of a prediction model. The fifth section reviews the previously published and commonly used methods of load prediction, ranging from linear regression, spectral expansion, to pattern recognition and auto-regressive integrated moving average modelling. Advantages and disadvantages of each method are also discussed. Estimation for special events such as television pick-ups and holiday effects is also presented. A brief summary is given in the last section of the chapter and it is concluded that the knowledge and experience of operators can be used to improve the overall performance of a predictor, which accounts for the need for expert systems.

The third chapter describes expert systems and the related techniques which include knowledge acquisition, knowledge representation, inference engine

and man-machine interface design. Much effort is being devoted to the application of expert systems to operation and control of power systems. Applications range from normal operation and control, such as load frequency control and reactive power/voltage control, to alarm processing, network fault diagnosis and system restoration. The last section of the chapter is focused on the application of expert systems to short-term load forecasting. It is concluded that expert systems can be used to improve the existing algorithms.

Chapter 4 proposes how expert systems can be applied to short-term load forecasting. A method of disaggregation of the overall load into its components is introduced in order to take into consideration the effective factors on electrical demand. Classification, disaggregation and estimation of each component are described in detail in this chapter. Testing has been made against the CEGB system load.

Chapter 5 presents the application of disaggregation of the overall load to prediction of the special case: effect of time change-overs (both from BST to GMT and from GMT to BST) on the load behaviour. Detailed description and explanation of load behaviour around time change-overs are given. It is proposed that lighting loads should be separately considered from the other components when predicting the time change-over effects. Comparison of this approach with other methods is also presented.

The sixth chapter presents load prediction of holiday periods. In this chapter, the loads in the periods ranging from fixed bank holidays to the period between Christmas Day and New Year's Day are predicted. Results are compared with some other methods. Some corrections are made to the contribution of weather effects on loads. Comparison has been made with other methods, especially with that of relative gaps, in the chapter. The elimination of holiday effects on further predictions is also given in order to predict the normal loads under normal situations.

Chapter 7 describes how weather effects on load can be considered based on an auto-regressive integrated moving average predictor. Much effort is

devoted to weekend load prediction. For simplicity, maximum temperature is used as the only effective factor on weekend load for both the summer season and the winter season.

A summary is given and conclusions are drawn from the study. Discussion of possible improvements in the performance of load prediction, and future work related to load forecasting are also presented in the last chapter.

The appendices contain additional information not included in the main body of the thesis. Appendix 1 details some mathematical tools for analysing the properties of a time series: calculation of autocovariance and autocorrelation functions. Appendix 2 represents the performance of the overall package for short term load forecasting. Appendix 3 describes some examples of procedures written in POP-11 to perform prediction.

CHAPTER 2

CONVENTIONAL APPROACHES TO SHORT-TERM LOAD FORECASTING

2.1 Introduction

The system load is the sum of all the individual demands at all the nodes of a power system. Estimation of a power system load at a certain time in the future is necessary since generating plant capacity must be available to balance exactly any network load at whatever time it occurs. The system load behaviour is generally influenced by four major factors, namely, economics, time, weather, and random effects. In the long-term, the installation of new plants and network expansion is dependent on the estimation of the future peak consumer demand many years ahead. The demand is actually determined by social, economic, technical, and industrial factors, such as national product growth, population growth, electricity tariff, political constraints. Three basic methods are used for long-term load prediction, namely, trend forecasting, market forecasting, and economic load forecasting [15]. In the medium-term, the scheduling of fuel supplies and maintenance programmes are based on the estimation of load a few months ahead. Exponential smoothing, and regression methods are commonly used. In the short-term, the variation of the system load must be known so that prior adjustment can be made by the power station allowing for output requirements, limitations upon boiler fuel feed rates and constraints upon the generator's rate of output change. The loads are affected in the short-term by the day-to-day activities of consumers and also quite often influenced by the weather conditions. The prediction methods for this short-term load are based on the history of past network loads, system configurations, and corresponding meteorological conditions.

This chapter will review some literature on the conventional methods for short-term load prediction. First, section 2.2 describes short term load characteristics from normal situation to some special events. Sections 2.3 and 2.4 will present the data which are used for prediction, and some design features which need attention when developing a new model for prediction. Next, section 2.5 will introduce, in detail, some commonly used methods for short term load prediction.

2.2 Characteristics of system load

Since the consumption of electricity varies from time to time and some unexpected errors happen to the telemetry measurements, this makes it very difficult to predict the demand precisely. The demand, however, in the short-term, shows some characteristics, e.g., periodical variation and changing trends. Most mathematical models are based on these properties.

2.2.1 Intrinsic properties

From the record of demand (which is a discrete time series) for electricity from the CEGB's National Grid System, it is found that the half-hourly load exhibits strong daily, weekly and seasonal variations. In a week, the load starts to grow on Monday, then remains at a peak in the middle of the week, and decreases on Friday, then reaches a trough at the weekend (see Figures 2.1 and 2.2 of summer and winter weekly load profiles). Within a single day, the electrical load starts to increase in the morning to reach a morning peak; then, after a small decrease during the afternoon, reaches an evening peak again around dinner time after which it gradually decreases to reach a low value during the night. The daily load profiles also change with seasons (see Figures 2.1 and 2.2). During a year, they reflect the low demand in the summer months and high demand in the winter months, with a ratio of approximately 4:1 (see Figure 2.3) between winter peak demand and a summer night demand for the CEGB system [125].

TITLE: Load Characteristics

FIGURE: Typical Summer Week Load Profile

----- SUMMERWEEK.P;

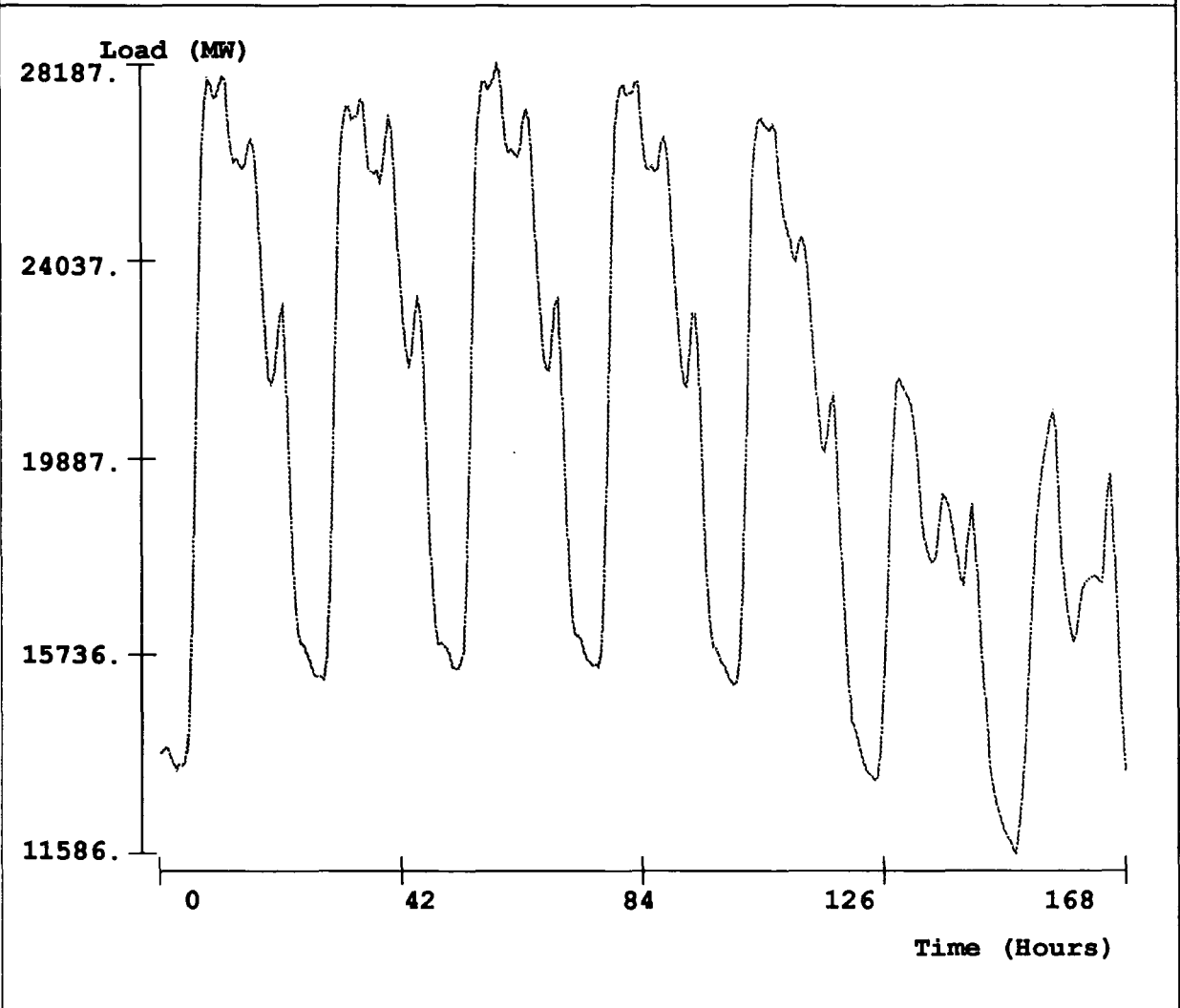


Figure 2.1 Typical Summer Week Load Profile

TITLE: Load Characteristics

FIGURE: Typical Winter Week Load Profile

— WINTERWEEK.P;

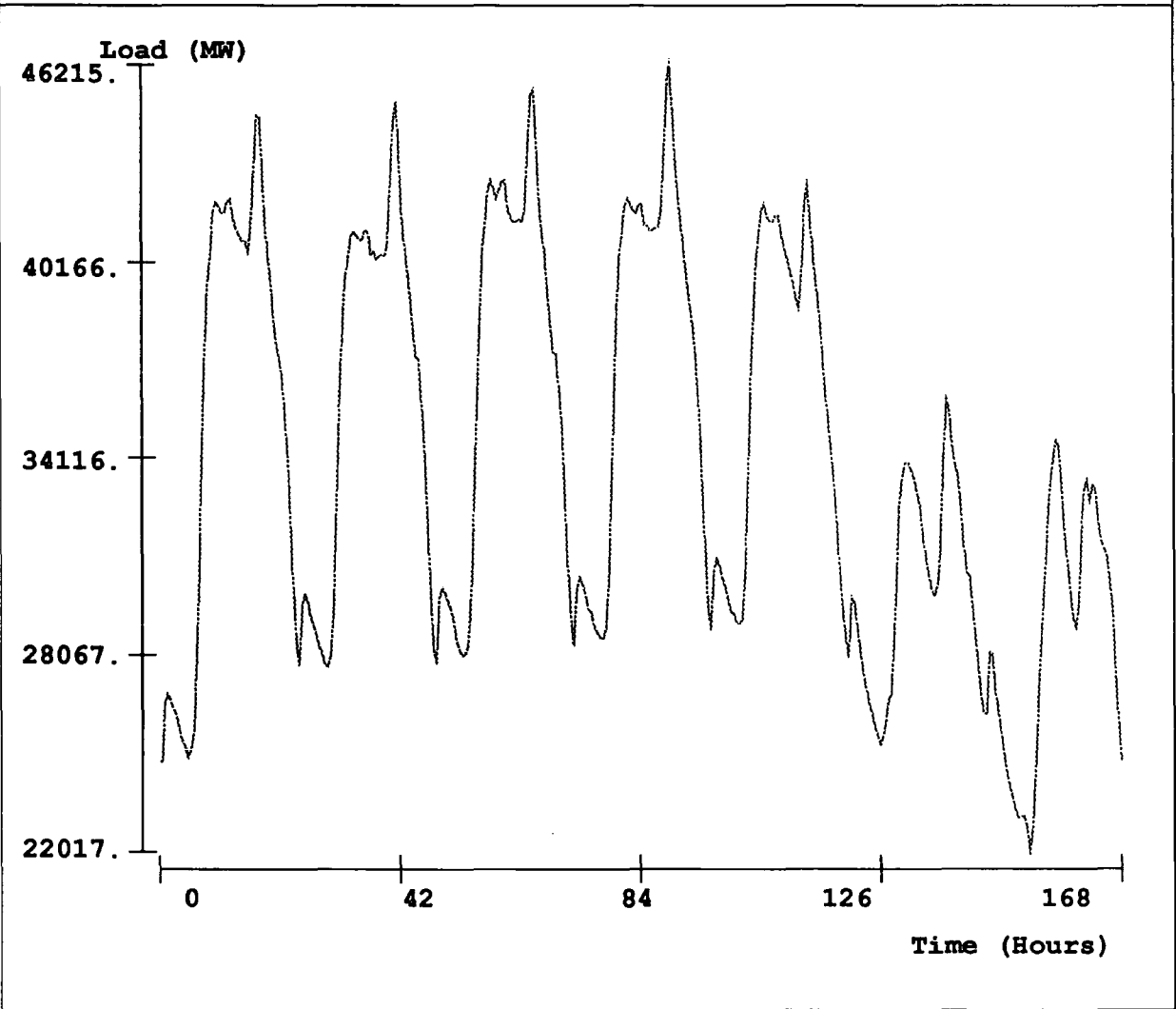


Figure 2.2 Typical Winter Week Load Profile

TITLE: Load Characteristics

FIGURE: Typical Daily Load Profiles in Summer and Winter

——— SUMMER.P;

- - - - WINTER.P;

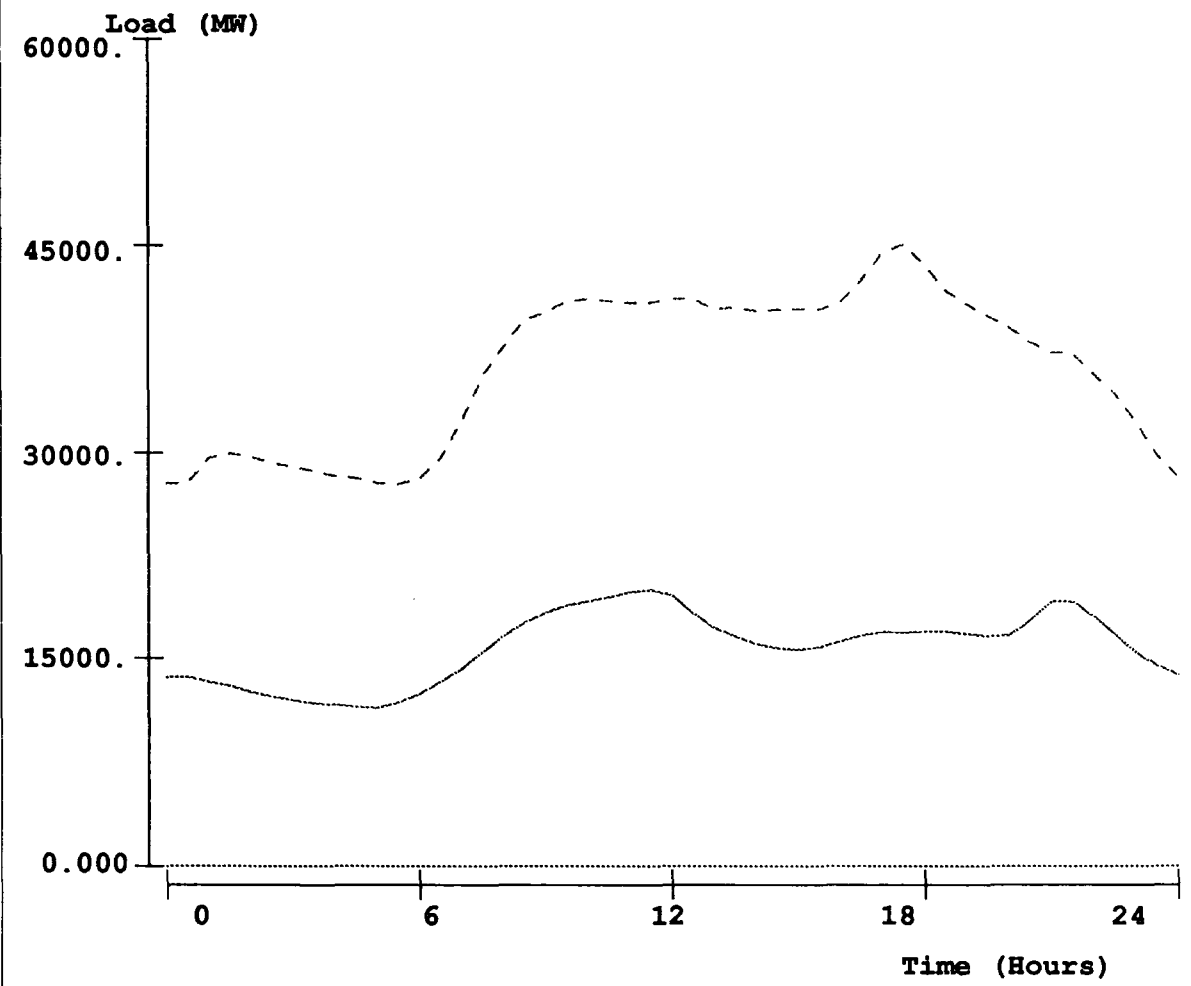


Figure 2.3 Typical Daily Load Profiles in Summer and Winter

The winter profile was the load recorded on 15 January 1985; The summer profile was that of 29 July 1984.

Furthermore, there is a growth pattern in the requirements that reflects the increasing load over time, either as a result of an increase in the number of consumers demanding power or an increase in the demand for power per consumer. An increasing number of consumers gives rise to a continuous growth which is only detectable over a relatively long period. This increasing trend can be ignored in short-term load prediction such as that of 2-3 hours ahead or even days ahead.

The periodical variation can also be shown by statistical analysis by the autocorrelation function (for its estimation, see Appendix 1). Table 2.1 shows the daily and weekly periods with autocorrelations of 0.815706 and 0.861754 respectively for the record of only two months of half-hourly data (from 1st of September to 31st of October in 1984 on the CEGB system).

Table 2.1 Autocorrelation Function with Time Lag

Lag-time k(days)	Autocorrelation Function
0	1.0
1	0.815706
2	0.635447
3	0.589124
4	0.582404
5	0.598889
6	0.730362
7	0.861754
8	0.698513
9	0.540044
10	0.500226

It can be seen from the table that the weekly cycle has stronger correlation

TITLE: Load Characteristics

FIGURE: Effect of Weather Conditions on Electrical Demands

——— L_10NOV.P;

----- L_17NOV.P;

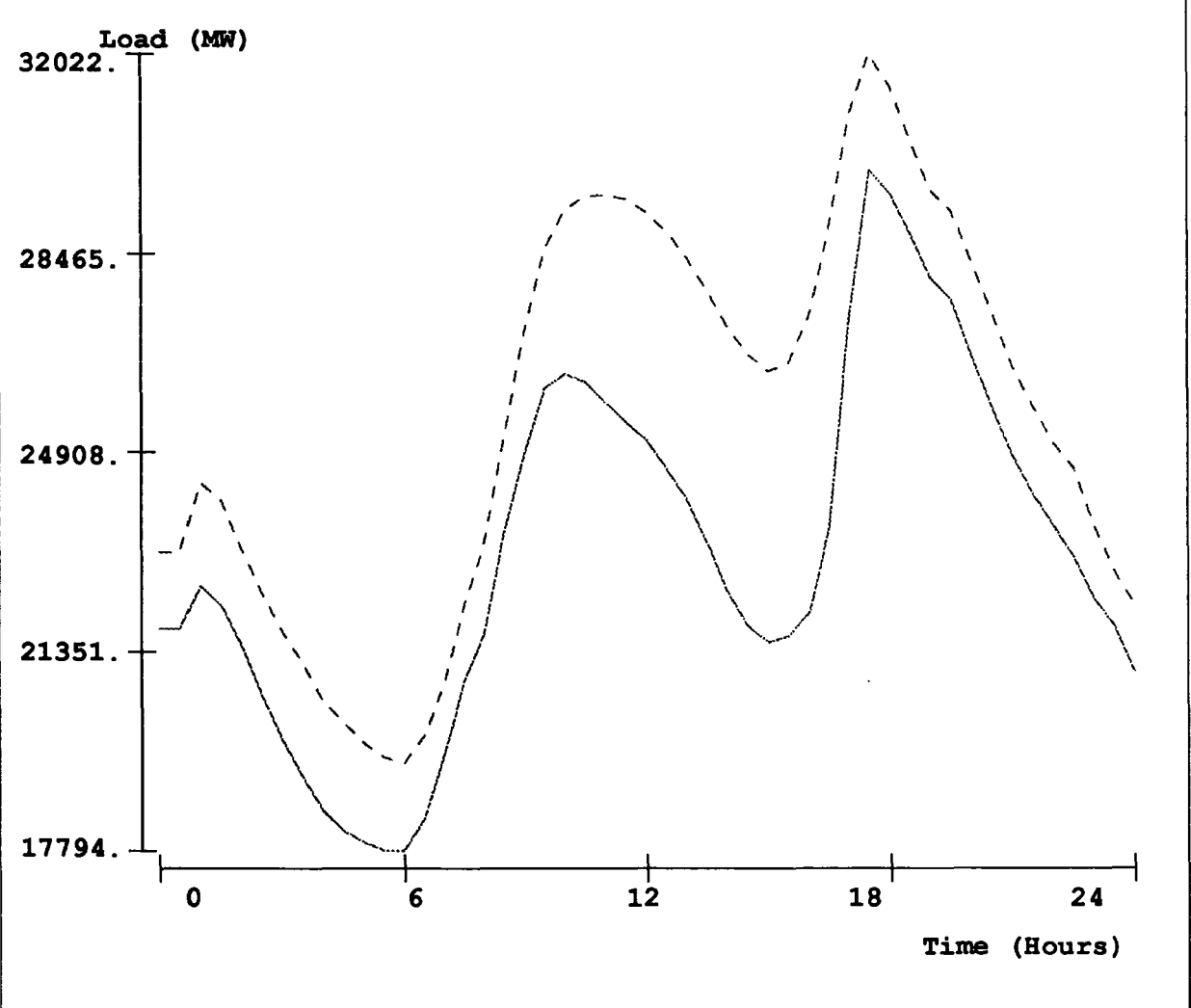


Figure 2.4 Effect of Weather Conditions on Electrical Demand

effects than the daily cycle. In other words, the load of any day-of-week resembles that of the same day-of-week in previous weeks, while the loads within a week do not replicate themselves from day to day.

2.2.2 Influence of weather conditions on load

Load behaviour is not only dependent on the time of a week, it is also significantly affected by weather factors, such as temperature, wind speed, humidity, since consumers' use of electricity for space heating, water heating, refrigeration, air-conditioning, and lighting is directly affected by those meteorological conditions.

Figure 2.4 shows a typical illustration of the weather effect on electrical demand based on the data of 10th and 17th of November in 1984 of the CEGB system (both days are Saturdays, the key weather data are in Table 2.2). For the CEGB system load, the weather effects are responsible for demand variations of up to about ten per cent around the average pattern [27].

Table 2.2 Weather Data and Load Data

for

10/11/1984 & 17/11/1984

Date	T_{max} °C	T_{min} °C	Wind-speed Knots	$Load_{max}$ MW	$Load_{min}$ MW	$Max(L_1 - L_2)$ MW
10/11/1984	14.3	9.8	3.3	29952	17794	21806
17/11/1984	6.6	3.3	6.1	32022	19348	26657

Note: $Max(L_1 - L_2)$ indicates the loads at time of maximum variation.

To identify the dominant weather variables, cross-correlation studies of average daily load versus daily weather variables such as temperature (maximum and minimum), humidity, light intensity, etc., can be carried out.

TITLE: Load Characteristics

FIGURE: Effect of Holidays on Electrical Demand

——— SUM_BANK.P; ······ POST_BANK.P;
- - - - PRE_BANK.P;

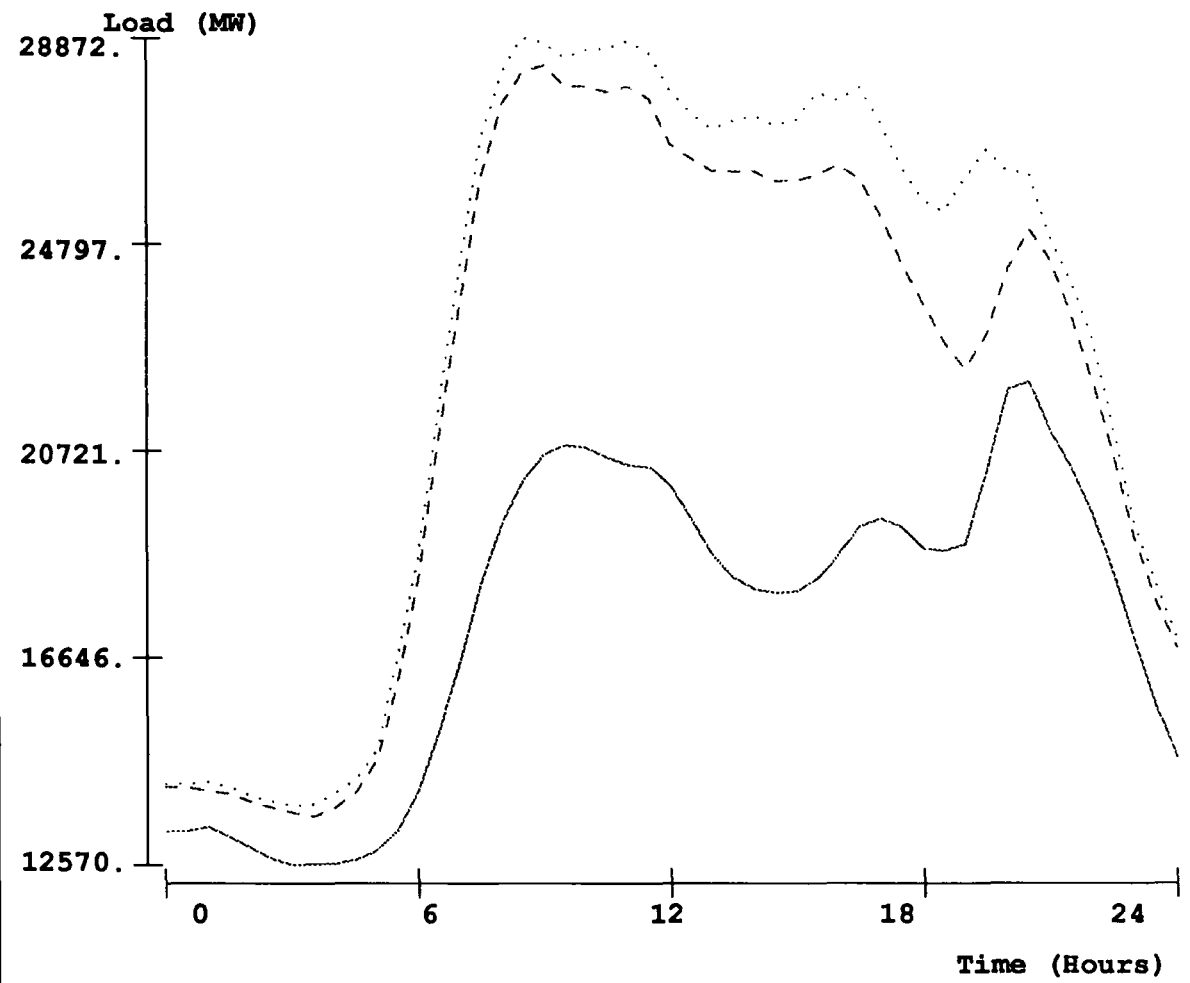


Figure 2.5 Effect of Holidays on Electrical Demand

In Great Britain [27], the dominant weather factors are: temperature, wind speed, and effective illumination (a function of cloud cover, visibility, and precipitation). In other countries, particularly those with a substantial air-conditioning component in the load, the additional factor of humidity (wet and dry bulb temperatures) will be important.

For this type of weather-sensitive load such external influences must be included in the model if more accurate prediction up to one week ahead is to be made. Obviously, the achievable accuracy depends on reliable weather forecasts. In practice, however, automatic updating of meteorological data at regular intervals is not easy.

2.2.3 Public holiday effects

In addition to weather factors, electrical load is also influenced by public holidays, such as Easter, Christmas Day, or even the regular Monday bank holidays. During these periods, the load is quite different from the normal load in both the shape and level. The holiday effects are not only on the holiday itself, but also on the **neighbouring** days during which industrial and commercial activity is shutting down or restarting. This can be seen in Figure 2.5 which indicates the difference of Summer Bank Holiday (27th August, 1984) from the same days-of-week of both the previous week (20th August, 1984) and the following week (3rd September, 1984).

In Figure 2.5, the load on the Summer Bank Holiday (27th August, 1984) was much lower than the load on the same day-of-week either of the previous week or the following week. Also the load profile was totally different.

2.2.4 Time change-over effects

The load record also shows that the consumer's use of electricity is affected by the time **change-overs** both from British Summer Time (BST) to Greenwich Mean Time (GMT) and vice versa.

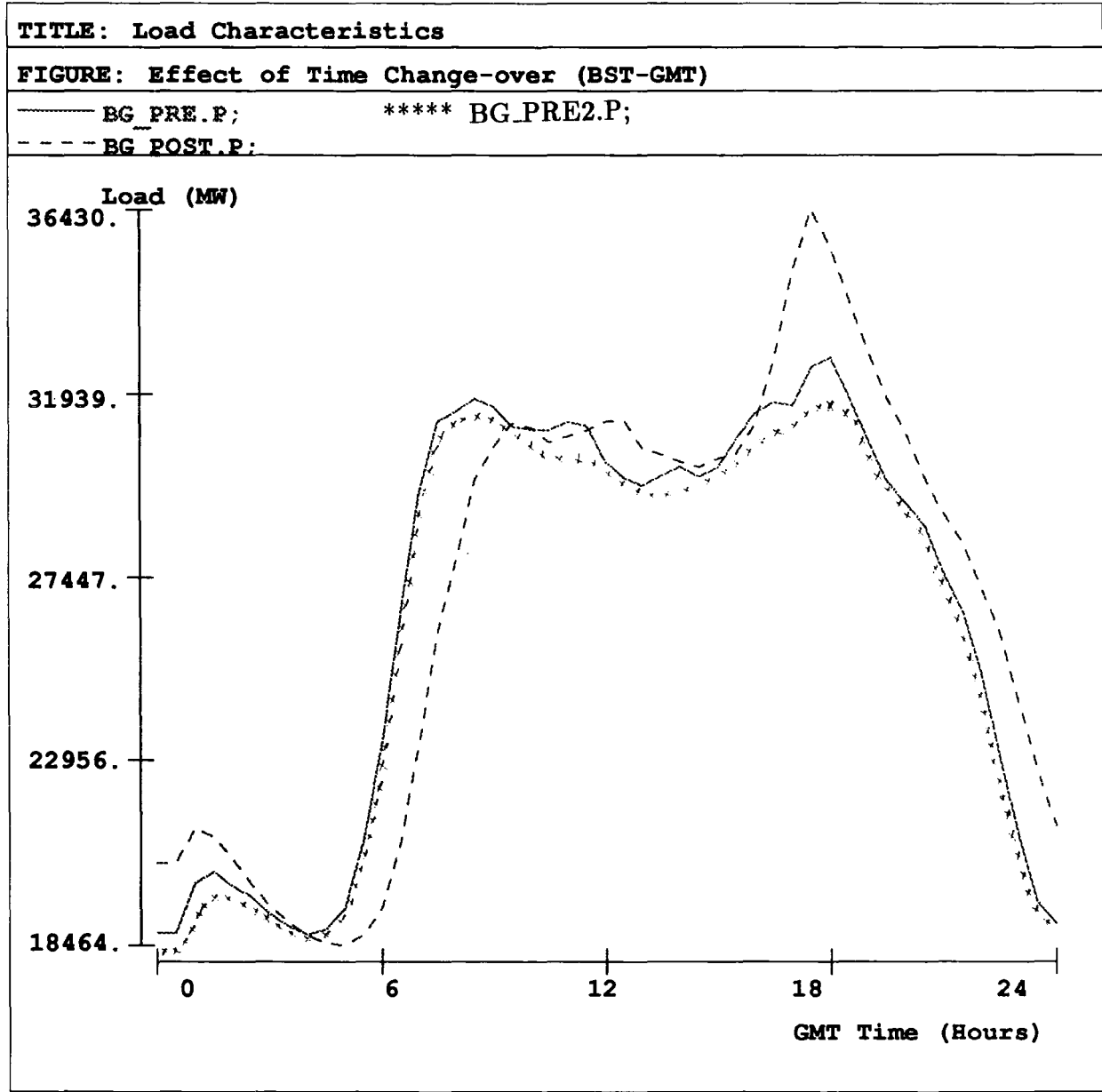


Figure 2.6 Effect of Time Change-overs (BST - GMT)

TITLE: Load Characteristics

FIGURE: Effect of Time Change-over (GMT-BST)

—— GB PRE.P;

---- GB POST.P;

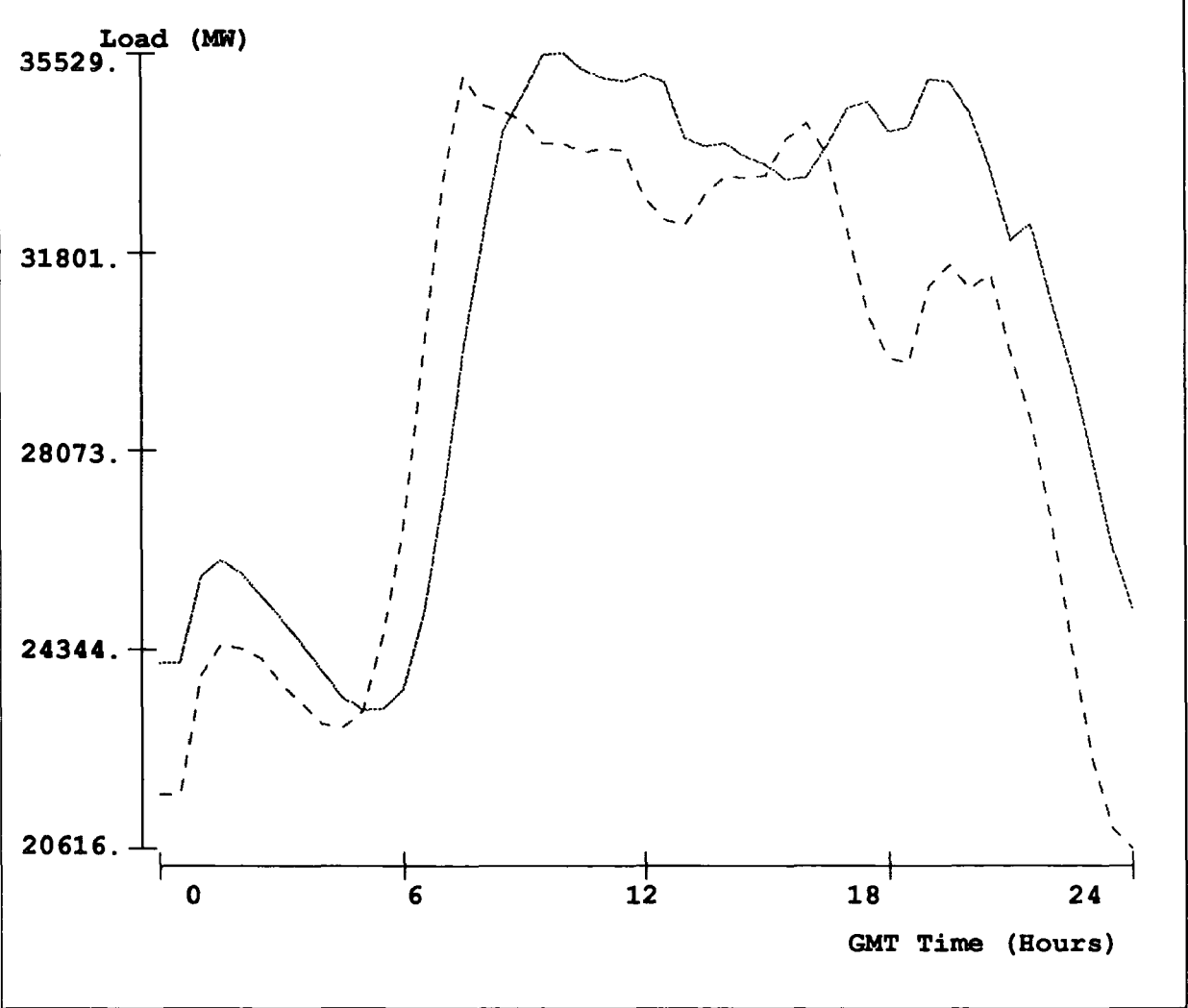


Figure 2.7 Effect of Time Change-overs (GMT - BST)

Figure 2.6 shows the effect of time change-over on loads from British Summer Time (Monday, 22nd October, 1984) to Greenwich Mean Time (Monday, 29th October, 1984). And Figure 2.7 shows the effect of time change-over from GMT to BST. The load profiles have been changed considerably in both cases. It is apparent that the variation is not as simple as a shift of load backward or forward by one hour (the difference of time change-overs). This aspect will be dealt with in Chapter 5.

2.2.5 Other special event effects

There are some other special events which can influence the load behaviour in addition to holidays and time change-overs. For example, during some evenings of popular TV programmes, e.g., of national significance such as the Royal Wedding, sporting events such as the Cup Final, the load has unusual sharp rises between the commercial breaks. This phenomenon is referred to as a "TV pick-up", defined [28] as the steep rise in the demand for electricity within about three to six minutes of a break in television programming. Every week there is an average of about 5 pick-ups of more than 500 MW and 40 pick-ups of more than 300 MW [28]. Pick-ups of less than 300 MW cannot easily be distinguished from normal system noise.

Moreover, the events such as widespread strikes and shutdown of industrial factories can also affect the system load.

As a result, all the irregular special events make it very difficult to perform accurate load prediction. However, many mathematical models have been developed for short-term prediction under normal situations.

2.3 Data requirements

Based on the properties stated above, the information needed for load forecasting should include:

The record of consumption of electricity (historical load data);

The record of weather data which should cover the same area and correspond to the same period as the load data, and the weather forecast covering the prediction lead time;

In addition to these two kinds of regular input data, some special information is also needed for accurate prediction, such as dates of special events, and the time schedule of popular TV programmes.

2.4 Design features

Since the system load is a random nonstationary process composed of thousands of individual components each of which behaves erratically without following any known physical law [88], all the models are empirical in nature and can only be objectively evaluated through extensive experimental evidence. So, the best test for a load forecasting scheme is its performance in the actual control centre environment over a period of time of at least two years.

The major components of a short-term load forecasting system are the model, the data sources, and the man-machine interface. Therefore, certain design features for the short-term load predictor have to be considered with attention focused on the following six major components[27]:

(1)Adaptiveness

In the forecasting model, not every parameter should keep the same value over time. This implies a need for automatic tracking of the parameter changes in the model.

(2)Recursiveness

Every time new data are available, forecasts need to be recomputed so as to update some parameters. This recomputation normally does not require tracking of the whole past history of the data, but rather, updating the

parameters based on new data. So it is necessary for a forecasting model to contain an automatic data updating function.

(3) Computational economy

Since the short-term forecast is for on-line operation and control, and usually the models have a large amount of historical load data and weather information to be manipulated, the algorithm needs to be economical with respect to execution time. This means that the computing time should be short enough in order to do planning before the event.

(4) Robustness

The forecasting model should be robust enough to be consistent over a long time even though it may be sub-optimal for part of the time series. The model should be able to detect errors in the incoming data since this will often include measurement errors. It should also be able to exclude anomalous data, because the existence of holidays and neighbouring days will violate the assumption of steady-state load behaviour. Those models which require the periodic input of extra variables, such as regular weather data inputs, should be robust against defaults in the input of new data.

(5) Accuracy of objective:

No prediction of the system load can reach perfect accuracy. The highest accuracy can only mean the smallest error which a good model presents in forecasting. Usually the root mean squared (RMS) errors are used to indicate the goodness of the model in fitting the load series:

$$RMS = \sqrt{\frac{1}{N} \sum_{t=1}^N (Z_t - \hat{Z}_t)^2}$$

where Z_t and \hat{Z}_t are the actual and forecast values, respectively, at time t ($t=1, 2, \dots, N$), and N is the total number of forecasts.

Some factors also affect the accuracy of prediction by any model. Typically, the seasonal change and lead time will cause a variation of accuracy. For example, root mean squared errors of prediction during winter and summer are about 1.4 per cent for lead times of three to four hours, and 2.5 per cent for lead times of 24 to 36 hours. These errors will increase to about 1.8 per cent and 3 per cent respectively during spring and autumn[27].

(6) Man-machine interface:

A good man-machine interface is necessary since forecasting systems have not been developed to a perfect stage and manual intervention from operators is inevitable.

Therefore, when a new algorithm emerges, all the above features have to be considered.

2.5 Conventional approaches

Since the problem of short-term load forecasting has been recognised as an important component in power system operation, many different models have been developed. Most of them are based on mathematical analytical methods and have been proven by researchers and operators to be reasonably accurate for different systems according to the specific characteristics of the system loads. Different classifications can be applied to them, such as univariate model and multi-variate model (depending on the number of variables); or regression model, pattern recognition, time series, etc., (based on the mathematical analytical methods); or some models using past load data only, but some requiring weather data inputs. Some models are built for prediction of peak load only. Here we introduce the methods classified by mathematical analytical models, since it is easy to expand one model, for example, from univariate to multi-variate, if it is understood how the method works.

2.5.1 Linear regression method

It has been noted that weather factors such as temperature, wind speed, cloud cover, and humidity, influence the load demand. Therefore, the whole load may be regarded [1, 32, 64, 92] as a composition of two parts: base load, and weather-dependent load. The weather effect is represented by a percentage of base load in order to predict the future load. According to some operational experience, typical weather weighting factors for temperature and cloud cover are listed in Tables 2.3 and 2.4, which are based on the CEGB system load [64, 140, 206].

Table 2.3 Weather Weight Variation with Monthly Temperature

Weight	December	April	May	June	July
	January	November	October	September	August
	February				
	March				
%	°F	°F	°F	°F	°F
10	15	25	35	95	100
8	20	30	40	90	95
6	25	35	45	85	90
4	30	40	50 80	50 80	85
2	35	45	55 75	55 75	80
0	40	50	60 70	60 70	75
-2	45	55	65	65	70
-4	50	60			65
-6	55	65			
-8	60				

The normal mean monthly temperature given by the UK Meteorological Office is used as a base for the temperature weights. Thus the normal mean

temperature of a month has zero weight.

Wind speed, by experience, has also been found to affect the consumption and typically a weight of +2% for each 5 m.p.h. of wind speed is used. The method has been found to be reliable given the base load pattern from day to day is uniform and the corresponding values for the same period on any day are again uniform.

Table 2.4 Weather Weight Variation with Cloud Cover

Weight	Degree of cloud cover
-2	Fair: broken fair-weather clouds reflecting sunlight
-1	Fair: scattered fair-weather clouds reflecting sunlight
0	Clear: blue sky
1	Fair: thin haze
1	Fair: scattered clouds high and thin
2	Fair: thick haze
2	Scattered clouds: low and thick
2	Broken clouds: high and thin
3	Broken clouds: low and thick
3	Overcast sky: clouds high and thin
4	Overcast sky: clouds high and thick
4	Light fog
5-6	Overcast sky: clouds moderately low and thick
7	Overcast sky: clouds low and heavy
8-9	Overcast sky: clouds very low and heavy
8	Moderate fog
10-12	Overcast sky: clouds very low, very heavy
10-12	Dense fog

The above consideration of weather effects is based on operational experience. Alternatively, the relationship between the weather-sensitive load and the weather conditions can be expressed explicitly in explanatory variables by a multiple linear regression method [3, 54, 92, 97, 197]. For a given time series, the explanatory variables are selected on the basis of correlation analysis of the time series. For example, a multiple regression model can be written as:

$$y(k) = a_0 + a_1x_1(k) + a_2x_2(k) + \dots + a_nx_n(k) + a(k) \quad (2.5.1)$$

where x_1, x_2, \dots, x_n are the explanatory variables for the times series of electrical load $y(\cdot)$. And a_0, a_1, \dots, a_n are the regression coefficients estimated by using least square estimation techniques; $a(k)$ is a random variable with zero mean and constant variance. The weather variables x_1, x_2, \dots, x_n can be different from season to season. That is to say, the variables should be checked based on the correlation studies when the season changes.

It can be seen that the effect of weather conditions on load behaviour can be expressed either in table form or in the mathematical formula of the regression method. The only difference is that the coefficients which indicate the relationships have been estimated in the form of tables by past operational experience, but have to be calculated by the least squares method based on the historical loads and weather data in regression analysis. Therefore, the regression analysis can update the coefficients adaptively while the analysis in table form is rather static. As a result, the regression method has an advantage over the table method that it can predict the load when the weather conditions are extremely abnormal (beyond the range listed in table form). However, any historical load or weather data errors will inevitably result in inaccurate coefficients and consequently prediction errors from the regression method.

Discussion:

The above method is only for weekdays, since the basic load changes very little from day to day of a week. On weekends, however, the load pattern is significantly different from that on weekdays, and consequently prediction for weekends should be treated separately from weekdays using a similar approach.

Since the relationships between electrical load $y(\cdot)$ and the influential weather variables $x_i(k)$ are not necessarily linear, a nonlinear transformation of the weather variables has been used [92, 127] to formulate a linear weather-load model. One of the many possible transformations for temperature is:

$$WV(i) = \begin{cases} TMP(i) - T_s & \text{if } TMP(i) > T_s \\ 0 & \text{if } T_w < TMP(i) < T_s \\ T_w - TMP(i) & \text{if } TMP(i) < T_w \end{cases} \quad (2.5.2)$$

where T_w and T_s are the fixed parameters and $TMP(i)$ is the average temperature on the i th day.

Based on a linear (or non-linear for transformation) regression method, some authors [97, 123] applied the following equation to predict daily peak load DPL:

$$DPL = B + CDF * WV \quad (2.5.3)$$

where:

B is the base load;

CDF is a vector of the cooling demand factors;

WV is a vector of the weather variables or weather conditions which influence the peak load.

Other effective factors, such as the rapid load fluctuations during and after television programmes, must be accounted for manually with the result that the success of the method depends, to a considerable extent, on the intuition and experience of the grid control engineer.

The prediction of effects of weather variables on load variations, either in table form, or in regression formula, requires regular weather inputs. Therefore, the accuracy of the weather forecast will affect the accuracy of load prediction. The advantage of the method is that the computation is economic

and very little storage is required, if the coefficients have been drawn up from historical data.

2.5.2 Spectral expansion method

Derived from the linear regression method, the spectral expansion method was first applied to short-term load forecasting by E.D.Farmer [70]. The electrical load is regarded as the combination of a long-term trend, a component varying periodically over each week and a residual component.

After the weekly and daily components are removed from the actual load, the residual fluctuations from day-to-day and hour-to-hour are mainly due to variations in the weather conditions:

$$y_{wd}(t) = A_w(t) + B_d(t) + X_{wd}(t) \quad (2.5.4)$$

where:

$y_{wd}(t)$ is the whole load at time t of day d in week w ;

$A_w(t)$ is the average weekly load at time t of week w ;

$B_d(t)$ is the average daily load at time t of day d ;

$X_{wd}(t)$ is the residual load.

$A_w(t)$ and $B_d(t)$ are obtained in the way:

$$A_w(t) = \frac{1}{ND} \sum_{d=1}^{ND} y_{wd}(t) \quad (2.5.5)$$

$$B_d(t) = \frac{1}{NW} \sum_{w=1}^{NW} \{y_{wd}(t) - A_w(t)\} \quad (2.5.6)$$

where:

ND: number of days in each week;

NW: number of weeks history.

The residual $X_{wd}(t)$ is a combination of functions of the effective meteorological parameters and can be expressed by linear transformation:

$$X_{wd}(t) = f_1(T_{wd})\beta_{wd}(t) + f_2(L_{wd})\gamma_{wd}(t) + f_3(W_{wd})\delta_{wd}(t) + \dots \quad (2.5.7)$$

where:

$f_1(T_{wd})$, $f_2(L_{wd})$, $f_3(W_{wd})$, etc. are functions of temperature T_{wd} , illumination L_{wd} , and wind speed W_{wd} , etc.;

$\beta_{wd}(t)$, $\gamma_{wd}(t)$, and $\delta_{wd}(t)$ are the weighting vectors for the effect of temperature, illumination and wind speed.

The discrete form of Karhunen's spectral expansion of stochastic processes was used to expand the residual loads $X_{wd}(t)$ in the form [70, 139, 140]:

$$X_{wd}(t) = \sum_{k=1}^K a_{mk} \lambda_k^{\frac{1}{2}} \phi_k(t) + \epsilon_m(t) \quad (2.5.8)$$

By minimising the mean squared error of the ϵ over the interval of samples, it is evident [139] that the λ_k and the transposed ϕ_k are the eigenvalues and eigenvectors of the matrix Q:

$$Q = \frac{1}{M} X^T X \quad (2.5.9)$$

where X is an (M*N) matrix of the residual components $X_{wd}(t)$. And the coefficients a_{mk} are statistically independent random variables with unit variance:

$$\sum_{m=1}^M a_m^2 = M \quad (2.5.10)$$

The predicative procedure is to calculate the characteristic functions from the long-term behaviour of the load and to determine the weighting coefficients a_{mk} by fitting the expansion to the immediate past. Having determined the best set of coefficients, the most probable values of future load may be derived given the most recent values of the past.

The whole procedure in matrix notation is:

- 1) Calculate the K largest eigenvalues, and the corresponding eigenvectors Φ of (2.5.9).
- 2) Partition the eigenvector Φ to form Φ_0 (of $p \times K$) and Φ_1 (of $(N-p) \times K$).
- 3) Calculation of coefficient matrix C .

Partition the load data for the day of prediction into known data X_0 (1, p) and required data X_1 ($p+1$, N):

$$X^T = [X_0 \quad X_1] \quad (2.5.11)$$

Since the coefficient matrix C can be derived from:

$$\Phi_0^T \Phi_0 C = \Phi_0^T X_0 \quad (2.5.12)$$

- 4) Prediction.

The predicted data X_1 will be:

$$X_1 = C^T \Phi_1 \quad (2.5.13)$$

Discussion:

1) An advantage of the spectral expansion method lies in the fact that no meteorological data are required for its predictions, and consequently, the need for expensive instruction or the use of possibly inaccurate weather forecasts can be avoided.

2) Another advantage of spectral expansion is that prediction can be made continuously for any hour of the day, without the need for storage or special graphs.

3) Matrix Q is symmetric, and Jacobi's method may be used for calculation of eigenvectors and eigenvalues.

The method can be used to predict the loads from $p+1$ to N , so the lead time of prediction is limited by the length of the data in a block N . That means, it can only predict the loads for the rest of the day given p known data.

Since Farmer's method only models the static relation between the load and weather factors, it is unable to take account of rapid and large weather condition changes and the changes which may be caused by the onset of electrical storms or television programmes of national interest, and the changes in consumer pattern on account of bank holidays or strikes.

As analysed by Matthewman [139] the mean squared error E of the prediction is:

$$E = \frac{1}{N} \left[\sum_{n=1}^N \frac{1}{M} \sum_{m=1}^M x_{mn} x_{mn} - \sum_{k=1}^K \lambda_k \right] \quad (2.5.14)$$

So, if the number N in a block increases, the error E will decrease. But, the increase of N will increase the computational time for calculating the eigenvectors and eigenvalues. In the equation (2.5.14), if the number of eigenvalues K increases, the error E can decrease as well. However, the dominant eigenvalue is much more significant than the second dominant eigenvalue, and the third. So, usually, only the first and/or second largest eigenvalues are used. Although the error E is proportional to $\frac{1}{M}$, the choice of M should not be too high, otherwise, the model will weight the eigenvectors too heavily towards the earlier data and will tend to give an inaccurate guide to future behaviour. A suitable number for M has been found by experience to be 20 [139].

Another point to be noticed is that the method is only for prediction of loads for weekdays. For weekends, Saturdays and Sundays, similar models must be built in similar ways. In this case, the choice of M will be very difficult because the load behaviour will be changed if M is chosen the same as for weekdays (which is 20).

In order to reduce the computational time, implementations have been made [206] in which the whole day can be divided into several periods. The same periods of past days are used to predict the future load within the period, but this limits the lead time of prediction (less than the period N).

2.5.3 General exponential smoothing method

The exponential smoothing method is widely used in forecasting the future sales of products. The earliest version of exponential smoothing, called "simple exponential smoothing", regards a time series as being made up locally of its level and a residual element. Since the available data consisted of a random sample, then the obvious thing to do would be to take a simple average of the observations, giving most weight to the most recent observation, rather less weights to the preceding observations. The way to achieve this is to employ a weighted average, with geometrically (exponentially) declining weights, so that the level of the series at time t is estimated by

$$\overline{X}_t = \alpha X_t + \alpha(1 - \alpha)X_{t-1} + \alpha(1 - \alpha)^2 X_{t-2} + \alpha(1 - \alpha)^3 X_{t-3} + \dots \quad 0 < \alpha < 1 \quad (2.5.15)$$

By substituting $(t - 1)$ for t in this expression and multiplying through by $(1 - \alpha)$, (2.5.15) yields

$$(1 - \alpha)\overline{X}_{t-1} = \alpha(1 - \alpha)X_{t-1} + \alpha(1 - \alpha)^2 X_{t-2} + \alpha(1 - \alpha)^3 X_{t-3} + \dots \quad (2.5.16)$$

By subtracting this from (2.5.15), then (2.5.17) will be obtained:

$$\overline{X}_t = \alpha X_t + (1 - \alpha)\overline{X}_{t-1} \quad 0 < \alpha < 1 \quad (2.5.17)$$

Equation (2.5.17) represents the basic algorithm for simple exponential smoothing: replacing the original X_t series by a “smoothed” series \overline{X}_t . The quality α is termed the “smoothing constant”. The forecasts of all future values of the series are given simply by the latest available smoothed value \overline{X}_t .

The advantage of the method is that it does not require the storage of all past values of a time series, all that is needed is the most recent smoothed value \overline{X}_{t-1} and the current observation X_t .

In practice, this simple exponential smoothing version is rarely employed. Instead, a more flexible version of trend, and (possibly) a seasonal factor in addition to the unpredictable residual element, has been developed.

First, a linear trend is added to the previous version:

Denote the estimate of level at time t by \overline{X}_t and of the trend by T_t , where

$$\overline{X}_t = AX_t + (1 - A)(\overline{X}_{t-1} + T_{t-1}), \quad 0 < A < 1 \quad (2.5.18)$$

and

$$T_t = C(\overline{X}_t - \overline{X}_{t-1}) + (1 - C)T_{t-1} \quad 0 < C < 1 \quad (2.5.19)$$

Then forecasts of future values of the series are given by $\overline{X}_t + hT_t$ of h steps ahead.

Second, a seasonal factor is considered:

If the seasonal factor F_t with seasonality S is multiplicative (while trend remains additive) to the equation (2.5.18), then

$$F_t = D\left(\frac{X_t}{\overline{X}_t}\right) + (1 - D)F_{t-S} \quad 0 < D < 1 \quad (2.5.20)$$

So, the present level is estimated by

$$\overline{X}_t = A\left(\frac{X_t}{F_{t-S}}\right) + (1 - A)(\overline{X}_{t-1} + T_{t-1}) \quad 0 < A < 1 \quad (2.5.21)$$

The three updating equations (2.5.19), (2.5.20), and (2.5.21) are used recursively for $t = S + 1, S + 2, \dots, n$. The forecasts of future values are given by $(\overline{X}_t + hT_t)F_{t+h-S}$ for h steps ahead ($h \leq S$).

If the seasonal factor is also additive, then the model and the updating equation should be changed accordingly.

In addition to the seasonal and/or trend factors, Muller [151] introduced an error difference smoothing of the last prediction to correct the current prediction.

The choice of the smoothing constants A , C , and D employed in the algorithms (and similarly the choice of α in the simple exponential smoothing formula) is discussed here. The lower the values of these constants, the more steady will be the final forecasts since the use of low values implies that more weight is given to past observations and consequently any random fluctuations in the present will exert a less strong effect in the determination of the forecast. In contrast, the bigger the values of these constants, the faster the response will be to sudden load changes. In practice, consequently, one will have to try to find the combination that fits the best.

Discussion:

It can be seen that the exponential smoothing method is economic, requiring both short computing time and little storage. The main disadvantage is that it can only predict loads of a very short time ahead (1-2 hours only, mostly used for half-hour ahead). The smoothing constants A , C , and D should be chosen carefully. It is foreseen that they cannot remain constant over 24 hours of a day in order to obtain best performance. Consequently, this method restricts the prediction lead times to a very short period, basically within 2 hours. Usually it is used to predict minute by minute loads [153]. In addition, it does not consider the meteorological conditions, which are the most influential factors in the load variations. Muller [151] proposed an example of including temperature in the model. The temperature-dependent load component is taken into account by changing the base load according to the coefficient of relative load change at a certain temperature:

$$X_i = X_{B,i} + X_{T,i} = X_{B,i}(1 + k_T(\gamma_{i-d})) \quad (2.5.22)$$

where:

$X_{B,i}$: base load;
 k_T : coefficient of relative load change;
 γ_{i-d} : temperature changes;
 d : the delay of temperature influence on load.

It is obvious that the method cannot forecast the effect of special events.

2.5.4 Harmonic decomposition method

Since the hourly (or half-hourly) load data for a given power system shows a distinct repetitive pattern with the repetition frequency of 168 hours (one week), provided that the variations due to seasonal effects and possible load growth are disregarded, the method of setting up a harmonic series model can be adopted for this repetitive weekly load.

Assuming that the variations of load pattern in a week are neglected, Fourier analysis can be used to express the past load data $y(t)$:

$$y(t) = b_0 + \sum_{i=1}^n (a_i \sin i\omega t + b_i \cos i\omega t) \quad (2.5.23)$$

where $\omega = 2\pi/168$ is the fundamental frequency.

The first problem is to identify the necessary harmonics ω_i that dominate the waveform, and the coefficients a_i, b_i . This can be achieved by the usual correlation and spectral analysis given a sufficient amount of past data.

Equation (2.5.23) can be written in a more convenient representation:

$$y(t) = f^T(t)a(t) + v(t) \quad (2.5.24)$$

where fitting function vector $f(t)$ and the coefficient vector $a(t)$ are in the following form:

$$f(t) = (1, \sin\omega_1 t, \cos\omega_1 t, \dots, \sin\omega_m t, \cos\omega_m t)^T \quad (2.5.25)$$

$$a(t) = (b_0, a_1, b_1, \dots, a_m, b_m)^T \quad (2.5.26)$$

The next problem is how to update $f(t)$ and $a(t)$ to perform prediction.

Function $f(t)$ is easy to update, since the trigonometrical functions in $f(t)$ can be updated by:

$$f(t+1) = Lf(t) \quad (2.5.27)$$

where the transition matrix L is given by

$$L = \begin{bmatrix} 1 & 0 & 0 & \dots & \dots \\ 0 & \cos\omega_1 & \sin\omega_1 & \dots & \dots \\ \dots & \dots & \ddots & \ddots & \dots \\ 0 & 0 & 0 & \cos\omega_m & \sin\omega_m \\ 0 & 0 & 0 & -\sin\omega_m & \cos\omega_m \end{bmatrix} \quad (2.5.28)$$

Since the weekly load pattern may have some variations from week to week, the coefficient vector $a(t)$ needs to be updated.

The early work [41] used the general exponential smoothing method to perform off-line updating of the coefficient vector since it considered $a(t)$ to be static. However, significant improvements can be obtained by using the Kalman filtering algorithm to update the coefficients [189].

Discussion:

This method does not require much on-line computational time and storage. It needs an off-line computation to increase the accuracy of the load forecasts by the method of exponential smoothing.

As stated before, the method only implicitly considers the static relation between the load and the causal variables of meteorological factors as Farmer's method does. The load variation caused by sudden and extremely large weather condition changes cannot be predicted by this method. Certainly it cannot be directly used for prediction of special events.

2.5.5 Pattern recognition method

Pattern recognition techniques are generally applied in the study of variables whose total physical principles behind their variations are unknown, but certain kinds of measurements explain their behaviour. Exactly expressing the total system load as a function of all the effective weather variables is impossible. Therefore, pattern recognition may be an ideal method to perform short-term load forecasting since the qualitative relationships between the load and the weather factors are easy to draw up. Matthewman and Nicholson [140] first introduced the techniques to load forecasting. It is based on the assumption that if a load demand has followed a certain pattern on account of a particular weather change in the past, it will tend to follow the same pattern if the same type of weather change occurs again.

One of the pattern recognition techniques is cluster analysis which tries to group objects which are characterised by attributes into different classes (clusters), such that the members of a class are most similar to one another, while the clusters differ mutually as much as possible. Euclidean distance was used to separate different classes. Weights can be given to different selected variables to enhance or reduce their relative importance and also to normalise different variables.

Matthewman and Nicholson [140] used the past load data x_1, x_2, \dots, x_n as attributes. The number of classes R is fixed by the accuracy of prediction.

For a peak load which varies between 2500 MW summer minimum and 4500 MW winter maximum, for example, approximately 30 classes would be required for a 2% accuracy. So, all the past data are classified into one of the 30 classes. The prediction of x_{n+1} is the next value in the class which has the least distance from the sample x_1, x_2, \dots, x_n .

Muller [152] classified the whole load into 6 classes: Monday, working day, Saturday, Sunday, Summer holiday and Winter holiday. The weekly and/or yearly cycles are eliminated by scaling the normalised values of the individual load.

Dehdashti [58] used the weather variables as attributes, which were determined by correlation analysis, to predict future loads by pattern recognition techniques. The choice of independent variables can vary dependent on the season being analysed.

Fu [76] introduced the learning regression method to consider the influence of meteorological factors. This used machine learning to try to find the load pattern for the same day-of-week with similar weather conditions in the history. This can improve the general forecasting performance, but too much storage is required.

Discussion:

Generally speaking, pattern recognition techniques can be applied to predicting any load as long as there are the same characteristic loads in the samples. But, the difficulty is how to correctly classify the attributes (for example, the historical data) into appropriate classes. It was found [140] that there were approximately 40 percent misclassifications in Matthewman and Nicholson's example. Another problem with the pattern recognition techniques is that they require excessive data storage to classify all sample points. It may be worthwhile to store the holiday load patterns as well as those of unusual events only, in order to predict the loads which possess similar characteristics.

2.5.6 Autoregressive Integrated Moving Averages (ARIMA)

This model is based on the Box-Jenkins [20] time series method. The load Z_t ($t = 1, 2, \dots, N$, equally spaced in time) is a non-stationary time series with strongly daily and weekly periodic cycles. The stationary series W_t can be obtained by the transformation:

$$W_t = \nabla^d \nabla_S^D (Z_t - \bar{Z}_t) \quad (2.5.29)$$

where:

\bar{Z}_t : the series mean obtained by

$$\bar{Z}_t = \frac{1}{N} \sum_{i=1}^N Z_i \quad (2.5.30)$$

W_t : the stationary time series with constant mean;

∇ : backward difference operator:

$$\begin{aligned} \nabla_S Z_t &= (1 - B^S) Z_t \\ &= Z_t - Z_{t-S} \end{aligned} \quad (2.5.33)$$

d, D: the difference orders:

$$\nabla_S^D Z_t = (1 - B^S)^D Z_t \quad (2.5.34)$$

B: backward shift operator:

$$B Z_t = Z_{t-1} \quad (2.5.31)$$

B^S : seasonal backshift operator of period S:

$$B_S Z_t = Z_{t-S} \quad (2.5.32)$$

Generally, (2.5.29) can be written as

$$W_t = \nabla_{S_i}^{d_i} (Z_t - \bar{Z}_t) \quad (2.5.35)$$

Then, the prediction problem has been reduced to represent the stationary time series by the autoregressive (AR) and moving average (MA) models as:

$$\phi(B)\Phi(B^S)W_t = \theta(B)\Theta(B^S)a_t \quad (2.5.36)$$

where ϕ , Φ , θ and Θ are polynomials in B such that

$$\phi(B) = 1 - \phi_1 B - \phi_2 B^2 - \dots - \phi_p B^p \quad (2.5.37)$$

$$\Phi(B^S) = 1 - \Phi_1 B^S - \Phi_2 B^{2S} - \dots - \Phi_P B^{PS} \quad (2.5.38)$$

are the auto-regressive components and

$$\theta(B) = 1 - \theta_1 B - \theta_2 B^2 - \dots - \theta_q B^q \quad (2.5.39)$$

$$\Theta(B^S) = 1 - \Theta_1 B^S - \Theta_2 B^{2S} - \dots - \Theta_Q B^{QS} \quad (2.5.40)$$

are the moving average components.

If p, P, q, and Q are correctly determined then a_t in (2.5.36) will be a white noise sequence distributed as $N(0, \sigma_a^2)$ where σ_a^2 is the variance.

The coefficients associated with each backshift operator in (2.5.37), (2.5.38), (2.5.39), and (2.5.40) can be derived by minimisation of the sum of squared errors a_t for all the sample points.

To ensure stationarity and invertibility of (2.5.36), the coefficients in equation (2.5.37), (2.5.38), (2.5.39), and (2.5.40) must all lie outside the unit circle:

$$-1 < \phi_i < 1 \quad i = 1, 2, \dots, p \quad (2.5.41)$$

$$-1 < \Phi_j < 1 \quad j = 1, 2, \dots, P \quad (2.5.42)$$

$$-1 < \theta_k < 1 \quad k = 1, 2, \dots, q \quad (2.5.43)$$

$$-1 < \Theta_l < 1 \quad l = 1, 2, \dots, Q \quad (2.5.44)$$

The whole procedure of determining the model and performing prediction consists of four stages:

a) Model Identification

The purpose of this step is to model the load data series into a particular one, the seasonal periods S_i , the orders of differences d_i , the auto-regressive orders p_i , and the moving average orders q_i are to be determined.

Two approaches can be applied, i.e., simply examining the series graphically, or by auto-correlation function (ACF) at periods k apart of the series:

$$r_k(Z_t) = \frac{C_k(Z_t)}{C_0(Z_t)}, \quad k = 0, 1, 2, \dots, N_t - 1 \quad (2.5.45)$$

where $C_k(Z_t)$ is the auto-covariance function:

$$C_k(Z_t) = \frac{1}{N_t} \sum_{t=1}^{N_t-k} (Z_t - \bar{Z}_t)(Z_{t+k} - \bar{Z}_t), \quad k = 0, 1, 2, \dots, N_t - 1 \quad (2.5.46)$$

where \bar{Z}_t is the mean of the series.

The values of $C_k(Z_t)$ approaching unity indicates potentially strong correlation.

In [100], the partial auto-correlation function (**PACF**), inverse autocorrelation function (**IACF**), and inverse partial autocorrelation function (**IPACF**), are used together in order to determine a suitable model.

b) Parameter Estimation

After S_i , d_i , p_i , q_i are determined, the model representing the load data series will be:

$$\Phi_i(B^{S_i})\nabla_{S_i}^{d_i}(Z_t - \bar{Z}) = \Theta_i(B^{S_i})a_t \quad (2.5.47)$$

Then the coefficients in $\Phi_i(B^{S_i})$ and $\Theta_i(B^{S_i})$ can be estimated by minimising the sum of the squares of residual a_t over the data samples, i.e., minimising:

$$a_t^T a_t = W_t \Phi_i^T(B^{S_i})(\Theta_i^{-1}(B^{S_i}))^T \Theta_i^{-1}(B^{S_i}) \Phi_i(B^{S_i}) \nabla_{S_i}^{d_i}(Z_t - \bar{Z}) \quad (2.5.48)$$

Any optimisation algorithms can be used, but the constraints are needed to check the stationarity and invertibility:

$$-1 < \phi_i < 1 \quad i = 1, 2, \dots, \quad (2.5.49)$$

$$-1 < \Phi_j < 1 \quad j = 1, 2, \dots, \quad (2.5.50)$$

$$-1 < \theta_k < 1 \quad k = 1, 2, \dots, \quad (2.5.51)$$

$$-1 < \Theta_l < 1 \quad l = 1, 2, \dots, \quad (2.5.52)$$

c) Diagnostic Check

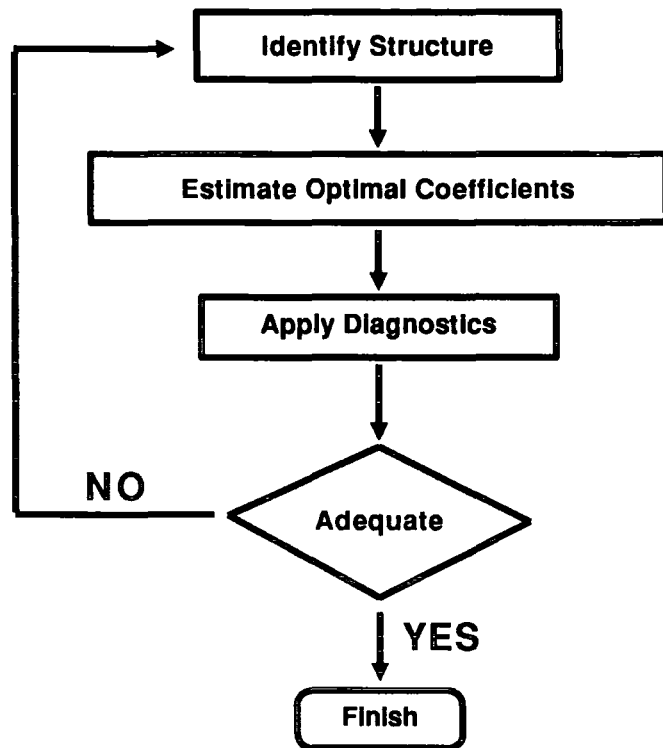


Figure 2.8 Structure of ARIMA

After the model has been preliminarily identified and the parameters have been estimated, the resulting residuals a_t should be a random normally distributed series (pseudo-white noise). That means there is no correlation of a_t in time. The autocorrelation $r_k(a_t)$, therefore, may be used as a check. If the autocorrelation $r_k(a_t)$ is not zero, then the model should be refined (back to stage a)).

d) Prediction

Having established a model of the time series W_t derived from the demand data over the period $t = 1, 2, \dots, N$ in the form of equation (2.5.36), this model may now be used for prediction by expanding it forward in time $t = N + 1, N+2, \dots, N + k$ with the assumption that the white noise error function a_t is zero for $t > N$.

The diagram for the whole process is shown in Figure 2.8.

The time series analysis has been adopted by many users [3, 65, 85, 94, 126, 127, 163, 169, 191, 208, 234]. It is adaptive and the prediction lead time can be as long as one week. The parameters can be updated as frequently as required. But off-line testing is needed to determine the periodical terms and the orders of the model to obtain the best prediction results.

Discussion:

Unfortunately, the univariate ARIMA model cannot predict the load variations due to sudden weather condition changes. Hagan [94] developed a multi-variate ARIMA model which can include the most influential weather variable of temperature:

$$y(t) = \frac{\omega(B)}{\delta(B)} X_{t-b} + \eta_t \quad (2.5.53)$$

where $\omega(B)$ and $\delta(B)$ are polynomials in B of orders s and r respectively, and X_{t-b} is the temperature.

This undoubtedly increased the number of parameters in the model and complicated the four stages. But unfortunately, the accuracy of prediction was not improved much compared with that of the univariate ARIMA model [94]. Instead, Hagan [94] used a third order polynomial of temperature to fit the load data of the ARIMA model and gained better results. Other authors [18, 65, 127] used the transfer functions of weather variables (temperature and illumination) to “correct” the load of both the historical data and the predicted data, if the weather conditions are different from the average conditions. The corrected data are modelled using a univariate ARIMA model.

In addition, the parameters are so sensitive to abnormal loads in the historical data that bad prediction for the future loads will result if there are some extremely special loads existing in the past. For example, if a bank

holiday exists in the period of data which are used to estimate the parameters, some unexpected prediction errors will result. So, in order to eliminate the effect of abnormal data, the model should be able to detect the abnormal data and replace them by normal data. Moreover, the model cannot predict the special loads, e.g., bank holidays. It is also shown by Gann [79] that the prediction accuracy will be lower when the prediction lead time becomes longer.

2.5.7 Unusual situations

Unusual situations here, refer to some special events which are, either not repetitive in the period of historical load data which are used for parameter estimation, or not random but disturbing and noticed by the operators. The most interested are the TV pick-ups and public holiday effects.

All the models stated above are generally based on normal conditions, either to represent the present (or future) loads in terms of the historical load data, and/or weather factors which have been shown great influence on load variations. Such models cannot predict the load for the case of special events such as TV pick-ups, or bank holidays.

Here, we present some special considerations for predicting TV pick-ups and public holiday loads.

2.5.7.1 TV pick-ups

“T.V. pick-up” is defined [28] by the C.E.G.B. as the steep rise in the demand for electricity within about three to six minutes of a commercial break in television programming. During popular television programmes, many households switch the electricity activity from other appliances to television. But at the commercial breaks or after the programmes, other electric appliances are switched on causing a steep load rise (as much as 1.9 GW [28]) which requires considerable use of standby units. The phenomenon has been studied by Bunn & Seigal [28] who concluded that as many as eleven “explanatory variables” influence the load rises. By analysing all programme changes in a

week, given 190 observations, they found the following regression formula to be the most encouraging:

$$PU = -70.4 + 443(LGHT) + 0.224(PTVR2) - 11.5(FTVR) + 1.79(LONG) - 48.7(TIME) \quad (2.5.54)$$

where:

LGHT: "lighting-up" - a 0-1 variable to indicate whether a programme coincided with the onset of darkness at sunset;

PTVR: the T.V. rating of the programme (individual, not household basis);

PTVR2: $(PTVR)^2$;

FTVR: the changing T.V. rating at the break in the programme for that channel;

LONG: the length of the programme;

TIME: a 0-1 variable to indicate whether a programme finished after 10 p.m..

It was concluded from the study that the regression studies can provide an aid to the operators. But the final decision is still based on experience of an expert analyst because predicting the T.V. pick-ups relies upon a combination of intuition and experience. Although the pick-ups occur in minutes, they will affect the smoothed half-hourly load data which are used as a part of the historical data for further prediction.

2.5.7.2 Public holidays

Electricity demand is considerably affected by public holidays, such as Easter, and Christmas holidays, or even the regular Monday bank holidays. The bank holiday effects have been shown in Figure 2.5.

Some methods have been developed for estimating holiday loads, which are based on modifying the models for prediction of normal loads. Srinivasan

[200] used the multiple correlation models of yearly, weekly and daily models for predicting normal loads. The holiday loads were forecast by neglecting the daily and weekly models and using the yearly model only which relates to the same holiday in the previous year. Alternatively, Meslier [94] used the ARIMA model for prediction of normal loads. Accordingly, he added correction factors to the ARIMA model to adjust for the holidays. This resulted in the number of parameters increasing up to 138. He also proposed a transfer function model in a form of ARIMA models with a period of 365 days. Brubacher & Wilson [24] proposed interpolating the unaffected demand observations from both before and after the holiday period. For the same holiday period over successive years, it is assumed that the ratios of the actual demand to the estimated normal demand are the same and can be used to forecast the effect on demand of future holidays. It is performed in the following way:

The holiday correction ratios were defined by:

$$H_t = 1 - \frac{Z_t}{\hat{Z}_t} \quad (2.5.50)$$

where:

Z_t is the actual demand value (affected by the holiday);

\hat{Z}_t is the interpolate, or estimate of the “normal” demand.

Although the historical load pattern varies in successive years, particularly over the important region where the demand is rapidly returning to its normal value at the end of the holiday period, the ratios seems quite stable in successive years.

After the ratios were obtained, the average value over the successive years is used for correcting the load forecast from the model which is used to predict the normal demand over the period of interest. This was done simply by multiplying by $(1 - \overline{H}_t)$:

$$Z_t = (1 - \overline{H}_t) * \hat{Z}_t \quad (2.5.51)$$

where \overline{H}_t is the average ratio of holiday effects of the previous years.

From these analyses, it is concluded that there is no perfect model which can predict both normal loads and unusual loads of special events.

2.6 Summary

Several short-term load forecasting models have been briefly explained and discussed. Different approaches are suitable for different cases of different system load. Some are good for very short lead times, since the approach reflects the very recent demand changes, while some are for longer lead times, as their performances are based on the reference of longer historical load profiles.

Since weather conditions have a key role in the variation of system load, load variations from any rapid large weather condition changes can easily be considered if the relation between weather conditions and load demand is explicitly expressed in the model. Usually, this kind of model (regression) is economic both in parameter estimation and load prediction, but the disadvantage is that it requires regular weather variable input.

The spectral decomposition expansion method has the advantage that it does not require any weather inputs and can implicitly represent the effect of weather conditions on electrical demand. The eigenvectors potentially represent the effect. In theory, the spectral expansion is the most suitable compared with other expansions in that it has the least errors over the period of interest. But in practice, not many users have adopted it because of the difficulty in choosing the parameters of M , K , N , and computation economy.

Pattern recognition techniques have encountered the problems of misclassification and too much storage.

Exponential smoothing and harmonic decomposition are not used as a forecasting model individually, but as a method of parameter updating and component detection respectively in time series and state space analysis.

Auto-regressive Integrated Moving Average (ARIMA) methods are the most widely used. Although off-line periodic component detection is necessary, the general prediction performance is relatively satisfactory. Because the methods have more weight on the recent past data than on the earlier data, the weather effect on load has been potentially taken into account in the model. Another factor to be pointed out about the method is that it should be able to detect the abnormal data in the past. Otherwise, the parameter estimation will be greatly affected by the abnormal data, and consequently, unexpected bad prediction will occur.

In conclusion, data requirements, accuracy of prediction, and economy in computation must be compromised to obtain a relatively satisfactory forecasting model which can be used on-line. From the viewpoint of functions, it has been seen that there is no such perfect model which can forecast loads for all situations of both usual and special events. The final decision of load forecast, especially for special effects, is made by the operators. This kind of experience and knowledge can be modified to be used by the computer, which is referred to as expert systems or knowledge-based engineering. Nowadays, expert systems have been (or being) successfully applied to many fields. It will be discussed in the following chapters how an expert system can be applied to load forecasting.

CHAPTER 3

ARTIFICIAL INTELLIGENCE TECHNIQUES

3.1 Introduction

It has been noted that the conventional numeric algorithms for short-term load prediction which were summarised in chapter 2 have encountered some problems which they cannot solve. The reasons are mainly either difficulty in expressing the exact relationship between the electrical load and the related factors, or lack of repetition in the period under consideration. For such circumstances as special events, the operator usually gives a prediction based on his experience, rather than on the results of the models. In a wider context, many engineering solutions and decisions are, in fact, made by engineers on the basis of their experience and skills, even when there are some specific algorithms existing in the domain. However, human experts are in short supply, very much in demand and expensive. Expertise can be lost through personnel changes due to job transfer or retirement. When it is available, it is slow and expensive to transfer to other humans. By contrast, artificial expertise is relatively inexpensive and once developed, it is easy to disseminate and can be operated at a low cost [174]. That is why engineers in more and more areas are in the process of building their own artificial expert systems. Can the computers follow and model what the behaviour of the operators for such cases? The answer is yes since a new branch of computer development, namely artificial intelligence (AI), has succeeded in applying the knowledge of human experts (the operators in our case) to different fields.

This chapter gives an introduction to artificial intelligence (AI) techniques and applications in general and its special application in power system operation and control.

The chapter is arranged as follows. In section 3.2, an introduction to AI is presented. In section 3.3, a brief summary is given about some related AI techniques: knowledge acquisition, knowledge representation, inference engine design and man-machine interfacing. Section 3.4 presents some successful applications of AI in power system operation and control, as well as in other fields. In section 3.5, we propose the application of AI to short-term load prediction. Finally, a summary and comments are given in section 3.6.

3.2 Introduction to expert systems

Artificial Intelligence was developed in the 1970s, when computer scientists generated types of systems, in which the programmes mimic human behaviour and reasoning, and perform tasks that previously could be performed only by human experts. These kinds of programmes can demonstrate some aspects of “intelligent” behaviour of human beings. Unfortunately, there is so far no perfect definition for AI. Basically there are three categories in AI systems: expert (or knowledge base) systems (and the tools to build them), natural-language (everyday native language) systems, and perception systems for vision, speech, and touch [171, 172]. Among them, the research and development of expert systems is the fastest growing branch. These systems use human-like reasoning processes to solve problems in specific problem domains, ranging from diagnosing certain infectious diseases, MYCIN [25], to prospecting for mineral sites, PROSPECTOR [96] and R1 for configuring VAX computer systems [96]. All these expert systems have been developed to investigate methods and techniques for constructing man-machine systems which can process the specialised expertise in a particular domain.

3.2.1 Types of expert systems

Expert systems are designed to solve problems on the basis of knowledge and expertise. Engineering problems can be categorised as interpretation systems, prediction systems, diagnosis systems, design systems, planning systems, and so on. Consequently, the expert systems can similarly be divided into the following categories [96]:

Interpretation systems infer explanations and descriptions from observables. An interpretation system explains observed data by assigning to them symbolic meanings which describe the situation or system state indicated by the observed data. This sort of system includes surveillance, speech understanding, image analysis, chemical structure elucidation, signal interpretation, and many kinds of intelligence analysis.

Prediction systems infer the likely consequences from given situations. A prediction system typically employs a parametric dynamic model in which the parameter values are estimated from the given situation. This includes weather forecasting, demographic predictions, traffic predictions, crop estimations, military forecasting and so on.

Diagnosis systems infer system faults or malfunctions from observables. The commonly used techniques are either based on logical associations between behaviour and diagnoses, or on the hypotheses of possible malfunctions which are tested against from the present observations. The generation of possible malfunctions comes from the combined knowledge of system design and that of potential flaws in implementation. This category includes medical, electronic, mechanical, and software diagnosis.

Design systems are used to develop configurations of objects so that the constraints of the design problem can be satisfied. Design systems construct descriptions of objects in various relationships with one another and verify that these configurations conform to stated constraints. In addition, many design systems attempt to minimise an objective function that measures costs and other undesirable properties of potential designs. Such problems include circuit layout, building design, and budgeting.

Planning systems design actions. These systems specialise in problems of design concerned with objects that perform functions. Planning systems employ models of agent behaviour to infer the effects of the planned agent activities. They include automatic programming as well as robot, project, route, communication, experiment, and military planning problems.

Monitoring systems compare observations of system behaviour to features that seem crucial to successful plan outcomes. These crucial features, or vulnerabilities, correspond to potential flaws in the plan. Generally, monitoring systems identify vulnerabilities in two ways. One type of vulnerability corresponds to an assumed condition whose violation would nullify the plan's rationale. Another kind of vulnerability arises when some potential effect of the plan violates a planning constraint. These correspond to malfunctions in predicted states. Many computer-aided monitoring systems exist for nuclear power plant, air traffic, disease, regulatory, and fiscal management tasks, although no expert systems for these problems have left the laboratory.

Debugging systems prescribe remedies for malfunctions. They rely on planning, design, and prediction capabilities to create specifications or recommendations for correcting a diagnosed problem.

Repair systems develop and execute plans to perform a remedy for some diagnosed problem. Such systems incorporate debugging, planning, and execution capabilities. These expert systems will find their applications in the domains of automotive, network, avionics, computer maintenance.

Instruction systems diagnose and debug student behaviour. They incorporate diagnosis and debugging subsystems that specifically address the student as the system of interest. Typically these systems begin by constructing a hypothetical description of the student's knowledge that interprets the student's behaviour. Then they diagnose weaknesses in the student's knowledge and identify an appropriate remedy. Finally they plan a tutorial interaction intended to convey the remedial knowledge to the student.

Meta-control systems adaptively govern the overall behaviour of a system. To do this, the control system must repeatedly interpret the current situation, predict the future, diagnose the causes of anticipated problems, formulate a remedial plan, and monitor its execution to ensure success. They include air traffic control, business management, battle management, and mission

control. The technology of knowledge engineering should handle many control problems which cannot be solved by the traditional mathematical approaches.

All these application systems are summarised in Table 3.1.

Table 3.1 Generic Categories of Knowledge Engineering

Category	Problem Addressed
Interpretation	Inferring situation descriptions from observables
Prediction	Drawing likely consequences on the given situations
Diagnosis	Inferring system faults and malfunctions from observables
Design	Configuring objects under constraints
Planning	Designing actions
Monitoring	Comparing observations to plan vulnerabilities
Debugging	Prescribing remedies for malfunctions
Repair	Executing a plan to administer a prescribed remedy
Instruction	Diagnosing, debugging, and repairing student behaviours
Control	Interpreting, predicting, repairing, and monitoring system behaviours

3.2.2 Components of expert systems

There are three fundamental components in an expert system: the knowledge base, the inference engine, and the control engine (see Figure 3.1). The knowledge base is the collection of domain knowledge in a specific area, containing facts (data) and rules (or other representations) that use those facts as the basis for decision making. The inference engine is the general problem-solving mechanism, containing an interpreter (interpreting the knowledge in the knowledge base) that decides how to apply the rules to infer new knowledge and a scheduler that decides the order in which the rules should be applied.

The control mechanism organises and controls the strategies taken to apply the inference process.

In building the expert system, there are some common features, such as how to extract the domain knowledge from the expertise, how to represent this knowledge in the form of programmes, how to make decisions and how to communicate with the system, etc.. They are referred to in expert systems as knowledge acquisition, knowledge representation, inference engine, and man-machine interface, respectively. They are essential in building an expert system.

3.3 Related AI techniques

In order to build an expert system or knowledge system which can act like a human expert, embedding the factual and experienced (heuristic) knowledge, the knowledge in the domain should be obtained first from the human experts and written into a form that can be used by a computer. So, the initial stage for building an expert system is knowledge acquisition.

3.3.1 Knowledge acquisition

Knowledge acquisition is the transfer and transformation of problem-solving expertise from some knowledge sources to a programme. Knowledge in an expert system may originate from many sources, such as textbooks, reports, data bases, case studies, empirical data, and personal experience. The dominant source of knowledge in today's expert systems is the domain expert [96]. Knowledge acquisition is a bottleneck in the construction of expert systems [239], since it is difficult for human experts to express their knowledge completely, accurately, and consistently under any circumstances. The primary way of acquisition is that the expert interacts with a knowledge engineer. The knowledge engineers usually have to use techniques to extract (decompile) the knowledge from the domain expert, such as on-site observation, problem discussion, problem description, problem analysis, system refinement, system examination, and system validation.

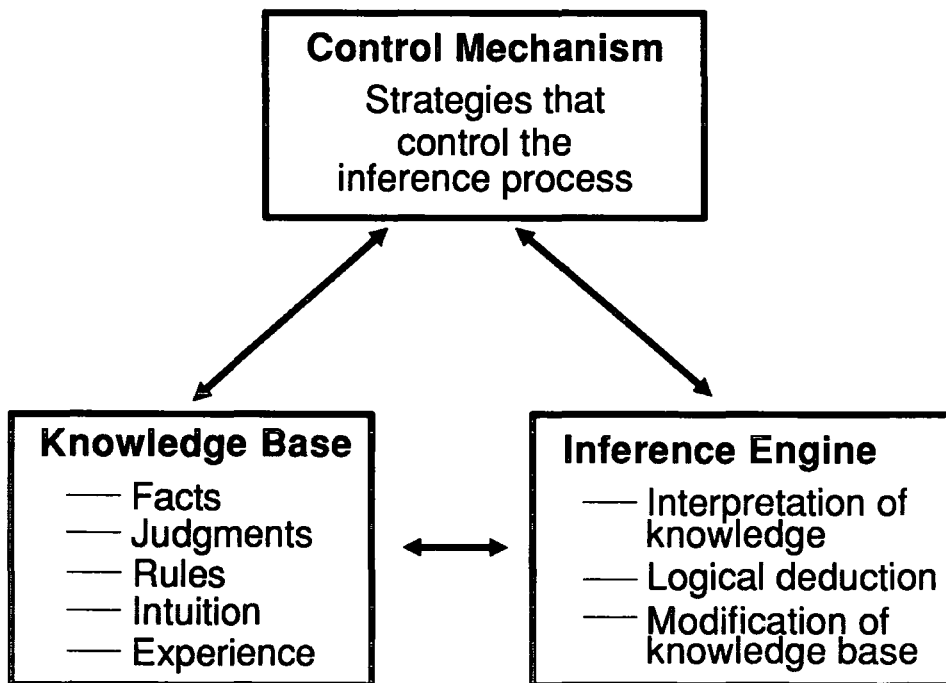


Figure 3.1 Components of Expert Systems

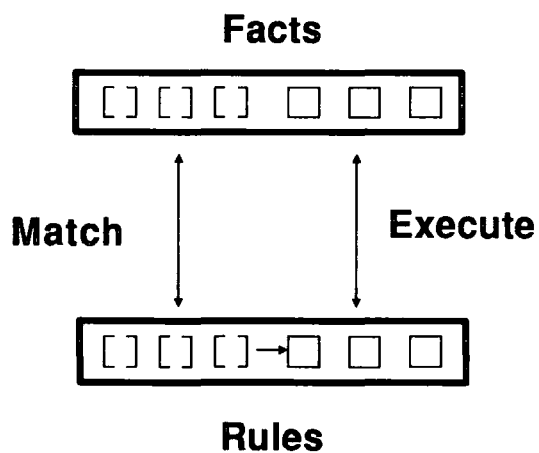


Figure 3.2 Execution of Rules

The second method of acquisition is a conversation between the expert and an intelligent editing programme, instead of a knowledge engineer [96]. The editing programme must have sophisticated dialogue capabilities and considerable knowledge about the structure of knowledge bases.

The final knowledge acquisition method is by acquiring the knowledge directly from textbooks [239]. This is the most ideal but difficult one as well since it needs a programme which can read a textbook and extract knowledge in a useful form.

The knowledge base is constructed on the basis of the knowledge acquired from the experts. An expert system relies completely on the knowledge base. So knowledge acquisition plays a basic but important role in building the system.

3.3.2 Knowledge representation

The acquired knowledge is usually not in a form which computers can directly use. So it is essential to encode the knowledge in an appropriate form so that computers can process it. There are two most common systems to represent knowledge in expert systems: rule-based systems and frame-based systems [239]. Frame-based systems include using semantic nets and frames.

3.3.2.1 Knowledge representation using rules

a) Production rules

The rule-based representation, the simplest and most popular type of knowledge representation technique, is to use the conditional **IF-THEN** statements in the form [74, 171, 239]:

IF a patient's age is less than 10 years old, and the patient has a fever greater than 103 degree Farenheit, and the patient has a skin rash, **THEN** there is suggestive evidence that the patient has measles.

When a rule is fired (or executed), the **IF** portion of the rule is satisfied by checking against a collection of facts or knowledge about the current situation, the action specified by the **THEN** portion is then performed (see Figure 3.2).

The advantage of using such production rules is that each rule can be readily changed in the light of new knowledge to improve upon the existing system.

b) Inexact reasoning

Sometimes, (for example in the example above, the “suggestive”), it is desirable to use a degree of uncertainty (inexactness) about the validity of a fact or the strength of a rule. There are usually three kinds of representation for this in expert systems: certainty factor (CF) [25, 74], probability theory [74], and fuzzy logic [74]. Thus, the rule, or fact needs one more portion for this uncertainty.

Certainty factor, a contribution of MYCIN, is a number devised by Shortliffe [25] for measuring the confidence that could be placed in any given conclusion as a result of the evidence so far. A certainty factor is defined [25] as the difference between two component measures:

$$CF[h : e] = MB[h : e] - MD[h : e]$$

where:

CF[h:e] is the certainty of the hypothesis h given evidence e ;

MB[h:e] is a measure of belief in h given e ;

MD[h:e] is a measure of disbelief in h given e .

Certainty factor CFs can range from -1 (completely false) to +1 (completely true) with fractional values in between, zero representing ignorance. MBs and MDs, on the other hand, can range from 0 to 1 only. Thus the CF reflects a simple balancing of evidence for and against the hypothesis.

MBs can be updated with new evidence:

$$MB[h : e1, e2] = MB[h : e1] + MB[h : e2] * (1 - MB[h : e1])$$

This means the effect of a second piece of evidence ($e2$) on the hypothesis h given earlier evidence $e1$ is to move the fraction of the distance remaining towards certainty indicated by the strength of the second piece of evidence.

Another approach to inexact reasoning is fuzzy logic (or “probabilistic logic”), was invented by extending classical logic to real numbers. In Boolean algebra, 1 represents truth and 0 is falsity. But, in fuzzy logic, in addition, all the fractions between zero and one are employed to indicate partial truth. For example,

$$p(tall(X)) = 0.75$$

states that the position that “X is tall” is in some sense three quarters true, one quarter false.

3.3.2.2 Knowledge representation using semantic nets

Knowledge can also be represented in semantic nets, which consist of points (called nodes) connected by links (called arcs). The nodes in a semantic net stand for objects, concepts, or events. The arcs represent relationships between the nodes.

Common arcs used for representing hierarchies include **is-a** and **has-parts**. The arcs establish a hierarchy of property inheritance in the net. Items in the lower net can inherit properties from items in the higher net (see Figure 3.3).

The net can be searched by using knowledge about the meaning of the relations in the arcs. Semantic nets are a useful way to represent knowledge in domains that use well-established taxonomies to simplify problem solving.

3.3.2.3 Knowledge representation using frames

A frame is a network of nodes and relations organised in a hierarchy, where the topmost nodes represent general concepts and the lower nodes more specific instances of those concepts [239].

The concept at each node is defined by a collection of attributes (termed slots in AI, e.g., name, colour, size) and values of those attributes (e.g., Smith, red, small). Each slot can have procedures attached to it which are executed when the information in the slot is changed (see Figure 3.4).

3.3.3 Inference mechanism

An inference engine contains knowledge about how to make effective use of the domain knowledge and how to select the relevant knowledge to reach a conclusion. There are two basic methods: forward chaining and backward chaining. Forward chaining is essentially a data driven strategy which starts from the initial data and ends up with the appropriate hypothesis. Backward chaining is a goal driven strategy which starts from an initial hypothesis and backtracks, fitting data to it, until sufficient data appear to disprove it or suggest it is an unfruitful avenue of investigation or alternatively prove the hypothesis. The most successful expert systems use a mixture of both forward and backward chaining.

In addition to an inference mechanism, knowledge systems generally also have a control mechanism [96], which controls the search and prevents the knowledge system from wasting its time exhaustively searching through irrelevant rules at random. Most commonly, the control mechanism is in the form of rules, known as meta-rules, either directing the order in which both

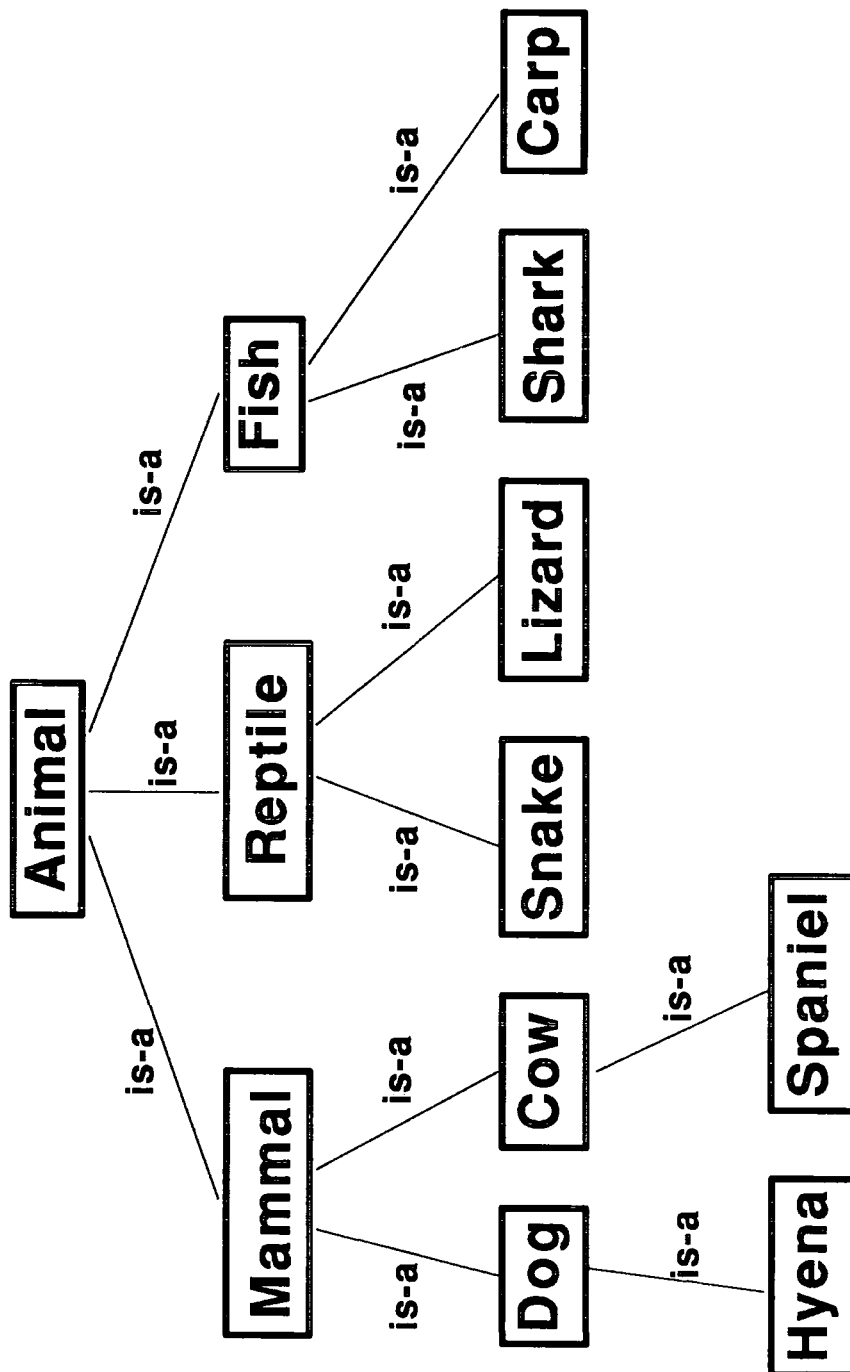
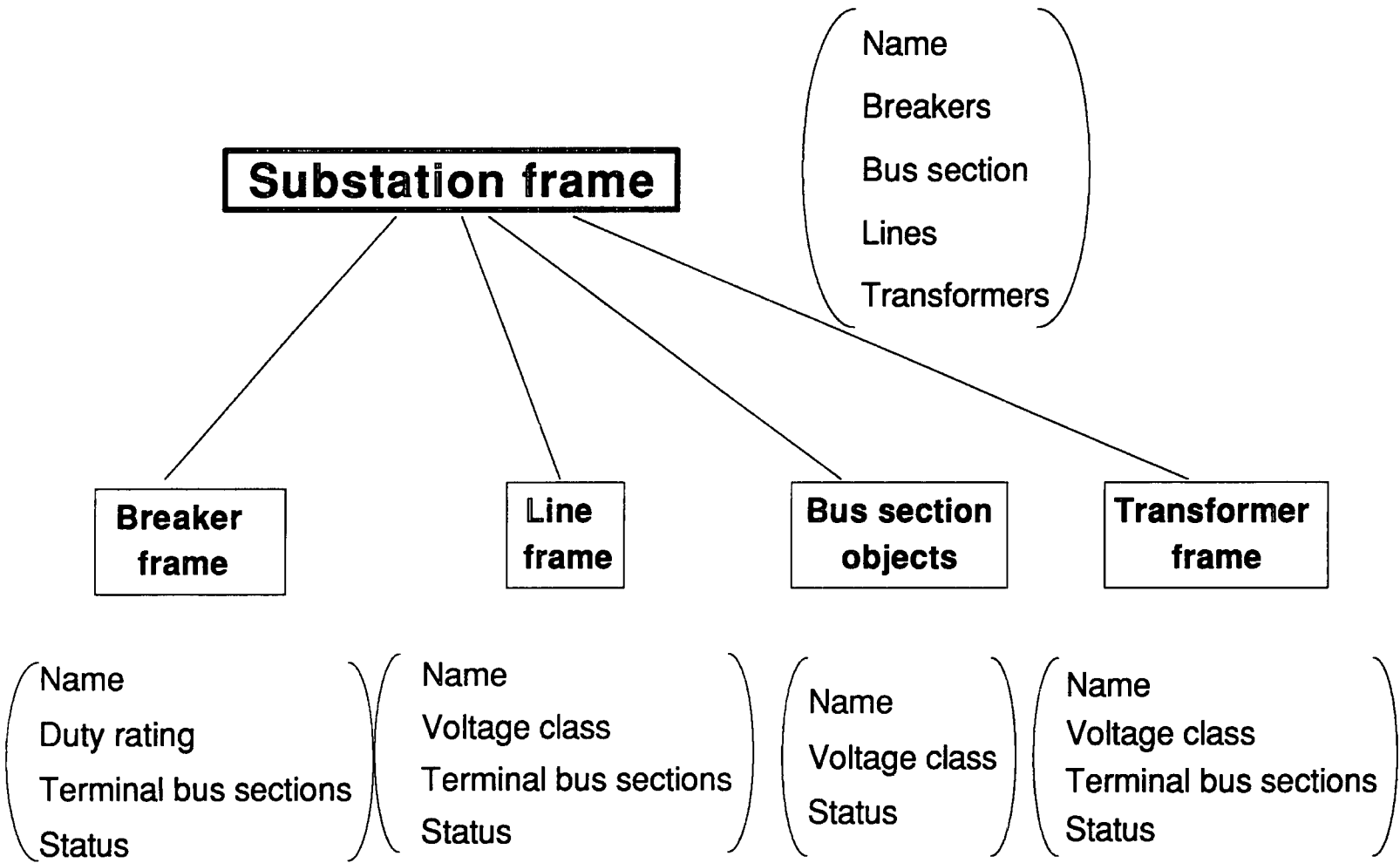


Figure 3.3 Representation by Semantic Nets

Figure 3.4 Frame Based Representation



hypotheses and different lines of reasoning should be pursued, or using heuristics to score the rules used to confirm the truth of a hypothesis.

3.3.4 Man-machine interface

The man-machine interface allows the user to interact with the system by putting forward the problem and observing how the system goes through a series of steps and arrives at a feasible solution [74]. The main thing about expert systems is that the user can question the system as to why it followed a particular course of action. This is much the same as the way a human expert can explain to us why particular options were taken up or ignored.

Since the expert system (or knowledge-based system) cannot completely replace the real human expert, intervention from the human is sometimes necessary. This requires an interface to provide appropriate communication between the human and the programmes.

These are the most important aspects we have to pay attention to when building expert systems. In the next section the application of expert system techniques to practical problems is presented.

3.4 Applications of expert systems

Some of the current knowledge engineering (KE) applications other than power system engineering are listed in Table 3.2 [96].

Among these applications, MYCIN is one of the clearest representatives for its high performance, flexibility and understandability. MYCIN is an expert system designed to provide advice through a consultative dialogue, and explain the reasoning of the performance system by certainty factors.

Table 3.2 Current KE Application

Application	Expert system	Objective
Chemistry	DENDRAL	chemical data interpretation & structural elucidation
	SYNCHEM 2	synthesis of organic molecules without human assistance
Computers	XCON	computer configuration
	YES/MVS	monitoring of the MVS operating system
Electronics	PALLADIO	design & test of new VLSI circuits
	ACE	diagnosis of faults in telephone network
Engineering	REACTOR	diagnosis and treatment of nuclear reactor accidents
	DELTA	identification and correction of malfunctions in locomotives
Geology	DIPMETER ADVISOR	interpretation of dipmeter logs
	PROSPECTOR	evaluation of mineral potential of a region
Medicine	MYCIN	diagnosis and treatment of bacterial infections
	INTERNIST/ CADUCEUS	multiple & complex diagnosis in general internal medicine
Others	HEARSAY	speech recognition
	MACSYMA	algebraic simplification & integration problems

Today, power systems have become more inter-connected, and more complicated. Their operation is time consuming not only for normal operation but also for the cases of emergency. Information arrives too fast in a power system emergency, so that it becomes difficult for operators to reach a correct

diagnosis of the problem and to formulate the correct decision when actions must be taken [251]. It is more and more essential to apply the techniques of expert systems with the expertise of experienced operators, as is stated in [135]:

- 1) As part of the real-time system, an expert system can be applied to give suggestion (an assistance) to the operators in time, based on the incorporated expert knowledge.
- 2) The knowledge required to perform a task can be represented in production rules, which is very close to natural language, therefore, it is easy for users to understand.
- 3) Each production rule represents a piece of knowledge relevant to the task, so it is very convenient to add or remove a rule when more experience is gained.
- 4) Each production rule can be provided with an explanation of why an action is taken under a certain situation.
- 5) It can be used to train and assist less experienced engineers and operators.
- 6) Expert systems can be integrated with mathematical modelling.

Expert systems are being developed in almost every branch of power system operation and control: load flow planning, load forecasting, network maintenance scheduling, contingency selection, unit commitment, reactive power and voltage control, system restoration, verification of switching sequences, alarm processing, and network fault diagnosis. Most of these applications are currently at the stage of prototype testing.

Here we briefly introduce the applications. Most applications use the rule-based representation as **IF-THEN** statements. The knowledge needed was acquired by drawing on literature and discussing with experts in the domain.

The applications usually need to interface between expert systems and numeric programmes. The expert systems are used to improve the numeric programmes and explain the results of the numeric programmes.

Reactive Power and Voltage Control

The traditional analysis for reactive power and voltage control is based on a contingency selection algorithm, i.e., considering single outages and double outages, etc. and then identifying the more severe ones for further study. It is obviously difficult to exhaust all possibilities for multiple outages, and because there exist heuristic rules in the area [135], the effective expert system can be utilised to help operators.

The knowledge-based approach [35, 39, 43, 135, 238, 258] to reactive power and voltage control is to apply heuristic knowledge to detect voltage problems and to decide the reactive power controls, such as shunt capacitors, transformer tap changes, and generator voltages, based on empirical knowledge. The facts are stored in knowledge base, such as the upper and lower limits of voltage at each bus, the upper and lower reactive power limits of each load bus. The production rules should also be stored in the knowledge base. For example [135],

If a load bus voltage drops below (or rises above) the operating limit, it is most efficient to apply the reactive compensation locally.

If the problem is so serious that empirical judgement may not be reliable, then the expert system will aid in formulating the problem in order to utilise an available software package which provides a more systematic method.

To identify the critical contingencies, some empirical rules are utilised to select the "important" outages. For example [135],

If the control compensator is at full output and there are no more controllers to be checked, then severity = emergency, and the reactive power dispatch algorithm should be utilised to find a feasible solution as quickly as possible.

By co-operation of expertise with analytical tools, the approach can reduce the computational burden and speed up decision-making time. The application [39] adopts a sensitivity factor for each bus voltage and control measure pair, and a weighting factor for each control measure. When one bus voltage is violated, the expert systems search sequentially for the most effective (the highest weighted sensitivity) control measure by using the sensitivity tree and calculate the control action needed to recover the voltage violation.

Network Fault Diagnosis

The most successful application of expert systems to power system operation and control is for network fault diagnosis [33, 113, 114, 143, 159]. Usually, the network fault diagnosis is performed by human operators on the information received from the breaker and relay signals. The experienced operators know the correlation between the operation pattern of protection relays, circuit breaker signals and the cause of the fault, and can recognise its location. They start using a hypothesis which explains changes in the network configuration and the sequence of events following the disturbance. When several faults have occurred or some pieces of equipment have malfunctioned, the fault diagnosis will become more complicated and consume more time. In this case, the conventional diagnostic technology seems less satisfactory. In order to diagnose faults accurately, effectively, and quickly, plenty of experienced knowledge and all kinds of information about the relays and breakers in the network should be combined and encoded in the expert system which can act like an experienced operator.

Two kinds of knowledge are represented in the knowledge base: the structure and function of each protective relay system and the human knowledge about the faults. For the former knowledge, the conjunctions of each element to be protected with the protective relays and breakers are represented usually in logic circuit form (called PROLOG facts [113]); For the latter knowledge, the rule-based system (called PROLOG rules) is used to represent the expertise, such as the patterns of different faults and the causes. As uncertainties exist in

the facts and rules, certainty factors, which are based on confirmation theory, are usually used for the inexact reasoning.

Firstly, all possible hypotheses about the location of the fault are generated. The inference engine searches the IF portion of the rules, by forward chaining, on the basis of the changed states of circuit breakers and relays. When a rule is found in which the IF portion is true, the rule is fired and a possible fault and its location are produced. For each hypothesis, the inference engine will search through the knowledge base, by the backtracking mechanism, until the hypothesis matches the present conditions which correspond to the observed data, or the hypothesis contradicts the present conditions. During the searching process, if some elements cannot be the location of the fault for an obvious reason, they are removed from the list of hypotheses. Each hypothesis is tested and ranked [119] based on the available relay signals. Finally, all the diagnosed faults are listed in the order of probabilities. Usually the pure PROLOG environment has been used as an inference machine [143].

Here is an example of a rule in this type of system [143, 159]:

**“IF the circuit-breaker failure protection relay operates,
THEN the location of the fault is in the protected area
of the relay which sent the trip command to the breaker
which failed to trip.”**

Meta-level control rules [215] can be used to dynamically guide the use of knowledge during the inference process. They can improve system performance by selecting rules or ordering rules. Malfunctions and failures [143] of relays and circuit breakers can be deduced from other information that the fault was within the zone but they did not operate:

**If a possible fault location belongs to the zone which the
relay X should protect, THEN there is a great probability
that the relay X failed to operate.**

Some special rules are needed to add to the knowledge base if there are some specially set relays which are different from normal due to system operational reasons.

So, the developed expert system can help to diagnose the various faults in the power system with reliable solution and fast processing speed.

After the fault is diagnosed, the relevant actions have to be done in the sequence:

- 1) Fault (short-circuit) found;
- 2) Protection system activated;
- 3) Trip order emitted;
- 4) Circuit breakers operated;
- 5) Apparatus isolated;
- 6) Fault eliminated.

Load flow problem

Because of solution methods, network conditions, and other operational factors, load flow packages are occasionally encounter problems of divergence, multiple, extraneous and false solutions. The application of an expert system [170] can improve the operators' use of power flow algorithms. Since the divergence phenomena are due to choice of initial conditions, system ill-conditioning and method of solution, the expert system can provide additional intelligence for the decision-making as dispatchers do. The knowledge employed in the expert system is from the experience of the dispatcher.

The knowledge base used in the expert system consists of **IF-THEN** rules which determine how the expert system will manipulate and process the input data. The inference engine manipulates the rules by making inferences. The conclusions are drawn up by the inference engine from the inputs. The production rules include rules about setting up, selecting methods and solution

types, evaluating telemetered information, assessing operational limits, determining network configurations, and avoiding erroneous conclusions. Operational rules, for example, can help to suggest the causes of divergence from the combinations of operational constraints. Rules are, for example, in the form of:

if the system mismatch power remains large as iteration increases,
and the Jacobian matrix is singular,
and the initial conditions are normal,
and all the network elements are not within their normal ratings,

then power flow runs diverge.

and

if the bus voltage is outside the operating limit,
and the power balance equation is not satisfied,
and critical lines are lost,
and the var support is in deficit,

then power flow solution is false.

So the indicators that cause divergence are set up to reduce the depth of mathematical analysis on a given network condition so as to reduce the computational time.

The rules are written in Prolog [148, 170], and the power flow calculation is in Fortran, so it is necessary to have an interface between Prolog and Fortran.

Load frequency control (LFC)

The aim of LFC is to maintain a continuous balance between electric generation and varying load demand by adjusting the output in real-time on regulating units in response to frequency deviation, and net tie-line power flow

deviation. Modern control theory has been utilised in the development of LFC algorithms. The proper type of controller and the control gain for optimal performance must be selected from among numerous combinations, based on the characteristics of disturbances and the load level.

An expert system has been applied for real-time load frequency control in a multi-area power system [157]. Empirical knowledge such as that required for selecting a control law and control gain tuning, are extracted and expressed in the form of production rules to determine the control command according to system conditions. The knowledge needed to identify disturbed area, select a control law, control gain tuning, treating control constraints, etc. is stored in the knowledge base. The knowledge-based system for multi-area LFC was developed and shown to allow selection of a proper type of controller and gain against various disturbances and load levels. It is expected to materialise a more flexible and robust control system which is not available from the conventional fixed controller structure.

Unit commitment

Unit commitment problems are generally solved by using dynamic programming and/or linear programming to select the most economical schedule of units for a study period by taking account of power system requirements such as unit maintenance schedules, minimum up and down time requirements, required spinning reserve, and ramp rate constraints. Because of the large search space and constraint complexity, the programmes need a very long period of execution time to obtain a schedule, which is sometimes found operationally unacceptable. In order to produce lower cost and operationally acceptable schedules, an expert system based consultant has been developed [147] to assist power system operators in scheduling the operation of generating units. The expert system incorporates the knowledge of the unit commitment programmer and an experienced operator. By consulting with the operator on some questions such as whether to bring a combustion turbine unit on, the expert system unit commitment can limit the search space and operational constraints in the unit commitment programmes. The inference engine used is based on that of

EMYCIN which is the MYCIN expert system minus its knowledge base. The expert system uses a set of rules provided by the knowledge engineer in the knowledge base to determine values for the parameters. The expert system supports forward and backward searching when a parameter is set to a new value or to try to find a value for a parameter. The expert system can also give explanation to the operator about the solution obtained by the programme.

By combination of the expert system and the unit commitment programme, lower cost and operationally acceptable schedules can be obtained.

Economic dispatch

The aim of thermal scheduling is to select generator units to be scheduled over a horizon of one day or more to meet the forecast system demand and spinning reserve requirement, by minimising the operational and fuel costs, subject to some operational constraints. Commonly used methods are based on mathematical optimisation programming techniques such as dynamic programming, mixed integer programming, and Lagrangian relaxation. Owing to the combinatorial explosion problem in scheduling the units, the process can be tedious and time consuming.

The scheduling problem can be interpreted as a tree searching problem. The tree representing the scheduling problem is searched by the depth-first and heuristic search techniques in artificial intelligence. The heuristic searching is based on the characteristics of the problem and the units while other operational constraints can be incorporated in the tree searching process to reduce the combinatorial explosion problem. Wong [254] has developed the heuristic search methods to schedule generator units in order to meet the rising load demand and spinning reserve for a day. For example,

Group capacity:

A unit in a group that has the largest amount of total capacity of generators yet to be scheduled on-line among all the groups is scheduled first.

Group selection:

At a scheduling point, a group from which a unit has been selected will have a lower priority for selection than the other groups at the next scheduling point.

The efficiency of the search can be increased by eliminating identical units in the searching set. After a valid schedule is generated, an alternative schedule can be found by backtracking.

In conclusion, use of heuristic rules can overcome the combinatorial explosion problem and determine the solution schedule with the lowest total generation capacity error at a higher computing speed.

System restoration

The objective of load restoration is that, when outages occur in the system following permanent faults, group restoration, zone restoration, and load transfer, and load shedding when necessary, should be undertaken within the operation constraints in order to restore a maximal number of zones. Therefore, it is under the assumption that the fault location has been already identified. The operators (dispatchers) have to consider many factors, such as the load requirements, frequency variations, system voltages, unbalanced conditions, protection, stability, and then plan a restoration scheme of switching actions. So in general, restoration is a heavy computation process.

The restoration process consists of the following aspects:

- 1) Finding out the initial source: from the adjoining power systems, or from the generation plants with black-start capacity;
- 2) Determining the restoration order of power stations;
- 3) Finding out the best restoration route;
- 4) Determining the strategies to connect the substations, and the switching actions.

However, when the system is in a critical (severe emergency) condition, the operator is likely to panic and make irrational decisions which could cause a greater emergency and eventually a catastrophe. By applying expert systems as aids [124, 134, 237], several patterns of network situation and action which were extracted from operational experiences and manuals are stored in the knowledge base. For example [134], the following rule may be stored in the knowledge base:

If a zone has more than one adjacent feeder, then the feeder with highest operating margin will be selected as the candidate feeder.

If load shedding is inevitable, the following production rules [187] can be used on the basis of operational experience:

If a bus has several overloaded lines, then determine the sum of flow reductions for incoming as well as outgoing overloads.

If for a given line, the amount of adjustment of the real power is known, then calculate the proper tap setting of the available phase shifting transformers, and determine the revised status of the power system.

When checking operating constraints, the calculation of load flow was undertaken by the conventional algorithms. So, the overall computer application usually involves the combination of FORTRAN for load flow calculation with PROLOG or LISP for the decision-making.

The expert system, which encodes heuristic knowledge, can give the great help to the dispatchers during system restoration especially under emergencies [60, 110, 210].

Transient stability

Transient stability studies are utilised to answer questions about disturbances on power systems, such as faults and sudden load or generation loss, that result in significant time-varying response, in the range of 0.01 to 20 seconds. The transient stability study of a power system concerns the following activities:

1. Study organisation;
2. Time simulation;
3. Output analysis;
4. Problem cause;
5. Specification of new tests;
6. Remedial measures.

The expert system is applied [6] in this way:

The knowledge base stores the knowledge in production rules (IF-THEN rules). Separate rule bases were provided for each of the activities, linking of information from one rule base to another was achieved where required. Since these rule bases are large and sparse, the inference engine was designed [6] in Fortran to incorporate special ordering procedures to ensure efficient processing. This ordering is achieved by assigning weighting and cost factors to each fact. If a fact is highly likely to be true, it is processed first. By contrast, if the

cost of evaluating a fact, in terms of computation effect, is high, then it is processed last.

Alarm processing

In an energy management centre, there are many alarm messages sent to the operators, which report the operation of breakers, the removal from service of pieces of equipment, or the excursion of key variables in the danger zones, such as current limit exceeded [8, 33, 119, 215, 252]. As stated in [119, 120], a power system operator must perform five tasks when he receives an alarm:

1. Become aware of the alarm;
2. Determine the events that caused the alarm;
3. Analyse the consequences of those events;
4. Review the sequence of events leading to the alarm;
5. Determining a course of action.

However, the operators may receive as many as 300 sustained alarm messages and 600 burst alarm messages per minute [33]. Conventional alarm processing systems suffer from limitations, which make it difficult for the operator to perform these tasks in a reliable and satisfactory manner:

- 1) Some alarm messages do not contain enough information;
- 2) Some alarm messages contain too much information;
- 3) Some alarms are needlessly repeated;
- 4) Multiple messages are generated for the same condition;
- 5) The number of alarms is sometimes overwhelming;
- 6) Some alarms are false.

With the help of expert systems built on the experience of the human operators, intelligent alarm processor can potentially provide the operators with a rapid reaction to emergency events by summarising information quickly and checking many more applicable rules than a human operator could in the same period of time. In the knowledge base, the alarms [250] are categorised as

breaker alarms, generation alarms, line/transformer status alarms, etc.. The production rules are categorised as alarm level rules, generation loss rules, suppress alarm rules, print alarm rules and special message rules. For example, some unimportant alarms such as that of indicating return to normal, can be suppressed. The line and transformer alarms which represent a worsening condition can be printed to operators.

By classifying the types of alarms and summarising them, the intelligent alarm processor can reduce the number of alarm messages and

- 1) Keep the operator aware of the most urgent alarms;
- 2) Keep the operator aware of problems as they occur;
- 3) Reduce alarm loading and present the strategic situation;
- 4) Provide the ability to perform a deeper analysis.

For example, for the alarms indicating breaker operation resulting from faults, the summary message [119] may indicate that a generator has been isolated or that a bus has been split.

Expert systems have also been implemented for many other aspects of power system operation and control, such as security assessment [42], contingency screening [205], dispatcher training simulation [48], and switching operations for substation monitoring [201], although these are at the stage of designing and testing.

3.5 Expert systems for short-term load forecasting

Most analytical methods developed for short-term load forecasting suffer from heavy computational burden because they need to process a great amount of historical data and/or weather information in order to build an appropriate model for prediction. Knowledge-based load forecasting has the advantages over the analytical tools of selective use of the data, the use of very recent data, and encoding system operator's expertise in analogous problem solving.

The knowledge is represented in production rules, and is extracted off-line based on human expertise and observations in most cases. Statistical packages have been used to support or reject some possible relationships between the changes in system load and changes in weather conditions. The rules are then stored in knowledge base; such as for different prediction lead times, appropriate algorithms are chosen; or for different seasons, the correspond prevailing weather data are used to represent weather-sensitive loads.

In order to store minimal data in the database, only typical load patterns for different seasons and days-of-week are used, as well as the prevailing weather data. The length of data is determined by knowledge, in order to avoid insufficient prevailing conditions and to alleviate computational burden.

Some intuitive knowledge is stored in the knowledge base, for instance, temperature rises will result in load decrease in winter, but load increase in summer.

Therefore, the potential for improvement in the load forecasting will be increased by greater knowledge about the characteristics of the system load.

The application of expert systems to power system short-term load forecasting is mostly to combine expert system techniques with the existing conventional programmes in order to develop a more sophisticated and accurate model. The techniques most widely used to date for short-term load forecasting has basically consisted of the analysis of time series using the Box-Jenkins methodology. The knowledge required is usually represented in the form of a rule-based system, and is used for considering special events such as national holidays, and popular television programmes.

For example, Park [160] used the Relative Gap to indicate the holiday load reduction:

$$R.G.(D, t) = \frac{Load(D, t) - M(D, t)}{M(D, t)} * 100\%$$

where $Load(D, t)$, $M(D, t)$ are the actual holiday load and ordinary load for day D at time t . This R.G. is usually used by the experienced operator to judge the holiday load when the prediction day is a national holiday.

Remior [174], in another way, used the production rule to select a holiday load curve:

If it is 1st November,
And it is not a Sunday,
Then assign the Autumn holiday load curve.

For television programme effects, a production rule is called such as [174]:

If it is a Wednesday in March,
And there is an important sports event on television,
And it is not a holiday,
Then correct hours 21 and 22 by a factor of 1.01.

So, it can be seen that these special event/day load demands are predicted by the human knowledge represented in production rules.

Although electrical demand is a random time series, it can be foreseen by appropriate analytical models and expertise. Different knowledge for different system loads can be built to assist the operator to perform prediction.

3.6 Summary

This chapter has presented the basic techniques in building an expert system such as knowledge acquisition, knowledge representation, inference engine design, and man-machine interfacing. Knowledge acquisition is needed to extract the expertise from the human experts, consequently it plays an essential role in building expert systems. The acquired knowledge must be represented in a way that computers can process. The inference engine is the central component, which contains knowledge about how to effectively use the domain knowledge

and to reach a conclusion. A man-machine interface is necessary as the users can sometimes question the expert system as to why the conclusion was reached. Also some systems need the user's intervention and data input.

All the applications in power system control and operation mentioned in this chapter have shown that an expert system can make use of the operators'/engineers' expertise and incorporate it with the existing specific algorithms in order to obtain better results. Knowledge-based systems can be successfully applied to fault diagnosis, due to the strong logical properties in the domain. It can be concluded from the authors' opinions that the more experience and expertise we have acquired, the more satisfactory results will be expected. Beside providing the final results, the expert system can provide the user with the explanation on how the results are obtained. Another important factor is that knowledge can be easily added to the knowledge base when more knowledge is acquired. The successful application of expert systems can improve the overall performance without the human intervention which is usually required by the more specific algorithms. Usually, the applications are on the basis of existing programmes (mostly in FORTRAN and C) and artificial intelligence languages, PROLOG (which provides the inference engine), LISP, and OPS5. Knowledge about the domains is represented in the form of production rules which can be easily understood by users. However, one has to bear in mind that the expert systems can never replace the human experts no matter how intelligent they are, because their knowledge is derived from the human experts.

CHAPTER 4

AN APPLICATION OF AN EXPERT SYSTEM TO SHORT-TERM LOAD FORECASTING

4.1 Introduction

Several numeric methods have been reviewed in Chapter 2 with respect to load prediction in the short term. These methods have been empirically shown to be rather satisfactory in predicting the electrical load for ordinary days under normal conditions. However, they are obviously unsuitable with the occurrence of unusual events, such as sudden changes of weather conditions and public holidays. In most cases, the effects of special events are normally predicted by human operators who use their operational knowledge and accumulated expertise. The recent development of powerful computers has enabled us to model human expertise by computers, which is referred to as **expert systems**. Chapter 3 has introduced some applications of expert systems to power system operation and control. The applications have shown successful and efficient use of expert systems if there is additional expertise and knowledge (deep knowledge) existing in domains in addition to shallow knowledge. This chapter will be devoted to establishing a new approach with the introduction of expert systems to short-term load prediction under unusual conditions. The form of this approach involves the disaggregation of overall electrical load into its composites, i.e., the individual loads for different purposes such as for lighting, heating, and industrial production. The need for disaggregating the overall electrical load and methods of doing this will be proposed and discussed in this chapter, particularly concerning how to define each component and how to estimate its weight in the overall load. The approach has been tested against the CEGB system load and the results are presented as well.

4.2 The necessity of decomposing the overall load into its components

Numeric methods for load demand forecasting may not accurately predict load for special events, partially because the events are not repeatable in the short-term (e.g., only one Christmas day in a year), or they are unable to take special events into their modelling (e.g., from GMT to BST). In addition, the effective factors such as the weather variables, exert different influences upon different parts of the overall load. That is why some numeric methods predict load by considering two major composite components: weather-insensitive and weather-sensitive loads. As for the weather-sensitive loads, however, they may not behave in the same way in correspondence with weather conditions. For example, commercial lighting loads are not so sensitive to cloud cover changes as domestic lighting loads are. In addition, implementation of load management has changed the utilisation of electricity of some electrical loads. It has been noticed that load management [16, 99] is to monitor and control some electrical utilities, for example, domestic heating, so that the overall load peak can be reduced. As a result, the use of expensive generating units which are needed to meet the peak load can be avoided and the overall operating costs can be reduced. Obviously, it is impossible to implement load management if the utilisation behaviour of individual loads is not obtained. The load affected by load management can be predicted only when each load is predicted on the basis of known behaviour and controlling strategy. Therefore, it is necessary to disaggregate the overall load into its components in terms of consumer types, such as industrial loads, commercial loads and domestic loads. These are defined as follows according to their general characteristics:

Industrial load: The largest part of the overall load is the industrial load. Basically this amount of load is consumed by large manufacturing and other large-scale process users. Types of heavy energy use are relatively few and the loads are usually localised at relatively few points in the system.

Domestic (Residential) load: This is the electrical load used by households. The load is dispersed over large geographical areas and consumed by a variety of small devices.

Commercial load: This is intermediate between residential and industrial loads. It may include a variety of residential devices which demand moderately large amounts of energy for lighting, heating and cooling large areas. Typical commercial load users are hospitals, shopping centres, banks, airports, small businesses, and hotels. Commercial load is dispersed more widely than industrial, but not so much as residential load.

Industrial and commercial loads are compared with each other in Table 4.1 [216].

Table 4.1 Total Consumption of Industrial and Commercial Customers with Demand of 1 MW and over (GWH) (1987/1988)

	1-10 MW	10+ MW	Total
Industrial	34,608	28,776	63,384
Commercial	7,954	1,229	9,183

Each kind of component can be further divided into its sub-components. For instance, domestic load consists of heating, cooking, lighting loads, etc.. As has been pointed out, each component changes at a different rate with different factors, some are weather-sensitive (e.g., lighting and heating loads), but some are not (e.g., industrial load). Typically around time change-overs, the industrial loads change as the working shifts are rearranged. Nevertheless, some loads like lighting loads are not affected so much by the time system change, but rather, the lighting-up time and cloud cover. If all these components can be estimated individually, the overall load can be computed by a weighted sum of the components [83].

4.3 Classification of electrical load

Based on the analysis as above, the overall load can be classified into different load sectors in terms of their major usage categories:

- Industrial sector;
- Commercial sector;
- Domestic sector; and
- Residual sector.

By analysis, each one can be further divided into subcomponents on the basis of end-use.

The industrial sector consists of:

- Industrial base load;
- Industrial lighting load;
- Industrial space-heating load;
- Industrial water-heating load.

The domestic sector is made up of:

- Domestic lighting load;
- Domestic space-heating load;
- Domestic water-heating load;
- Domestic cooking load;
- Domestic refrigeration load;
- Domestic entertainment load;
- Domestic clothes washing and drying load.

The commercial sector comprises:

- Commercial lighting load;
- Commercial space-heating load;

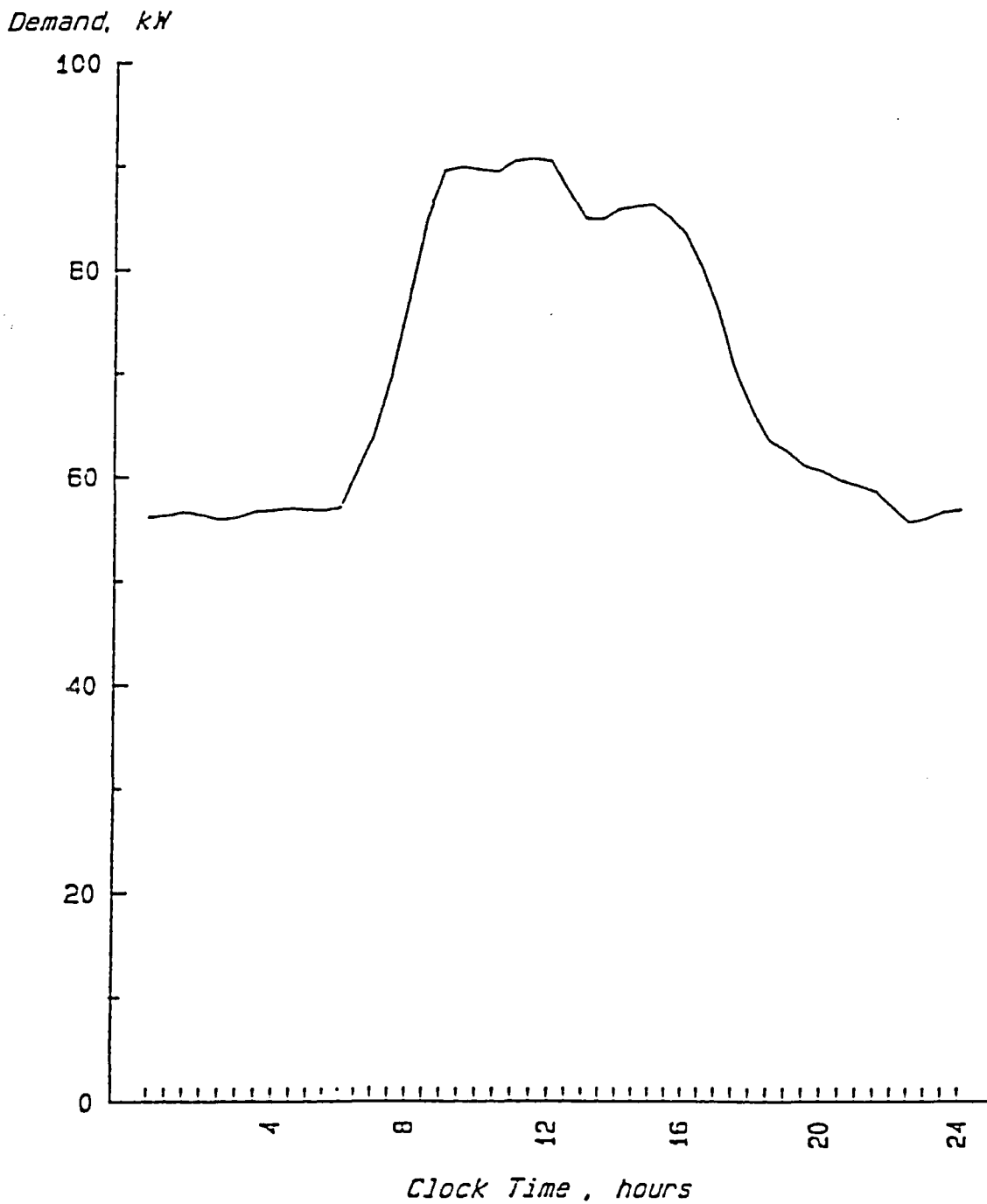


Figure 4.1 Typical Load Shape for Industrial Demand

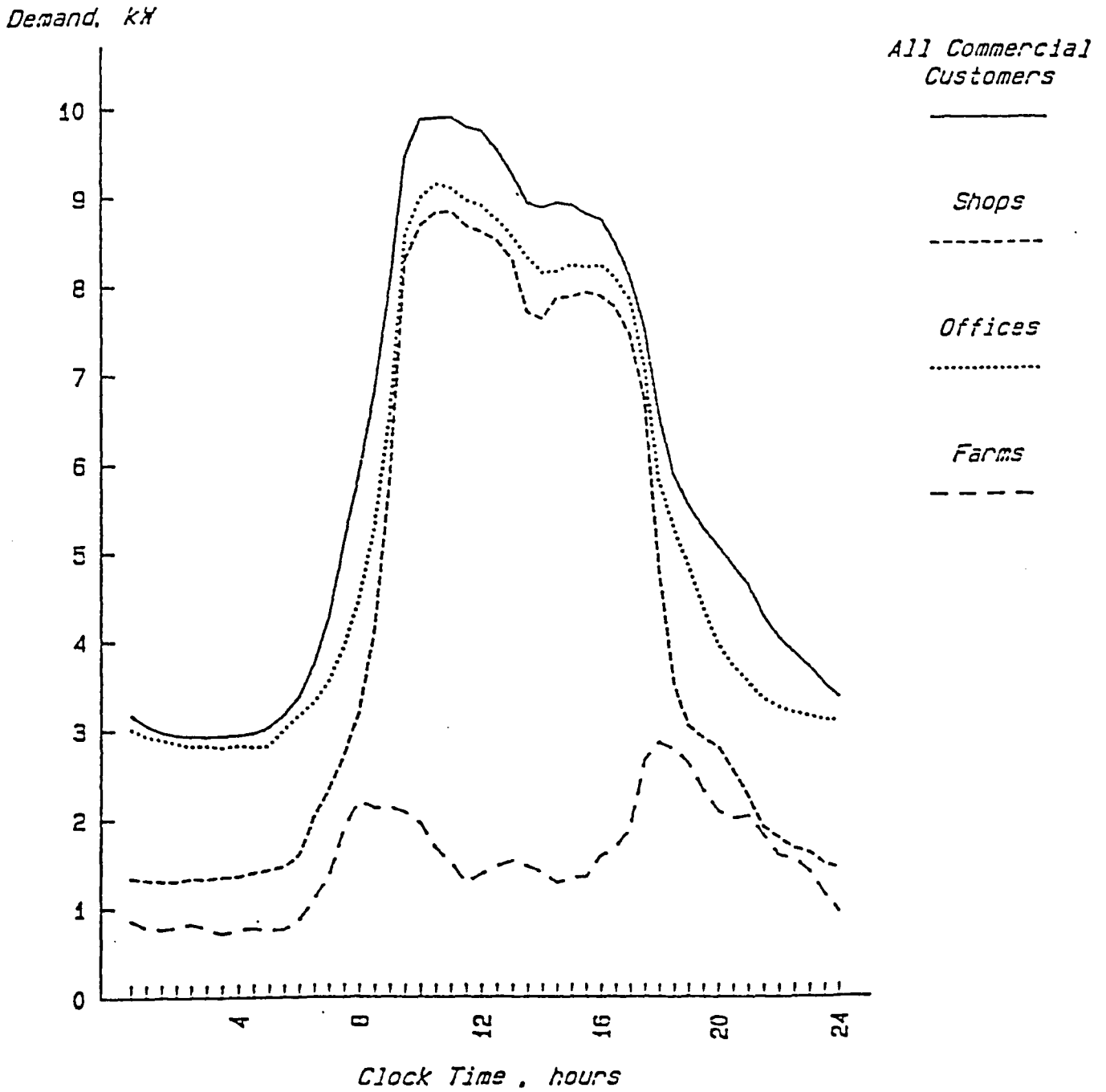


Figure 4.2 Typical Load Shape for Commercial Demand

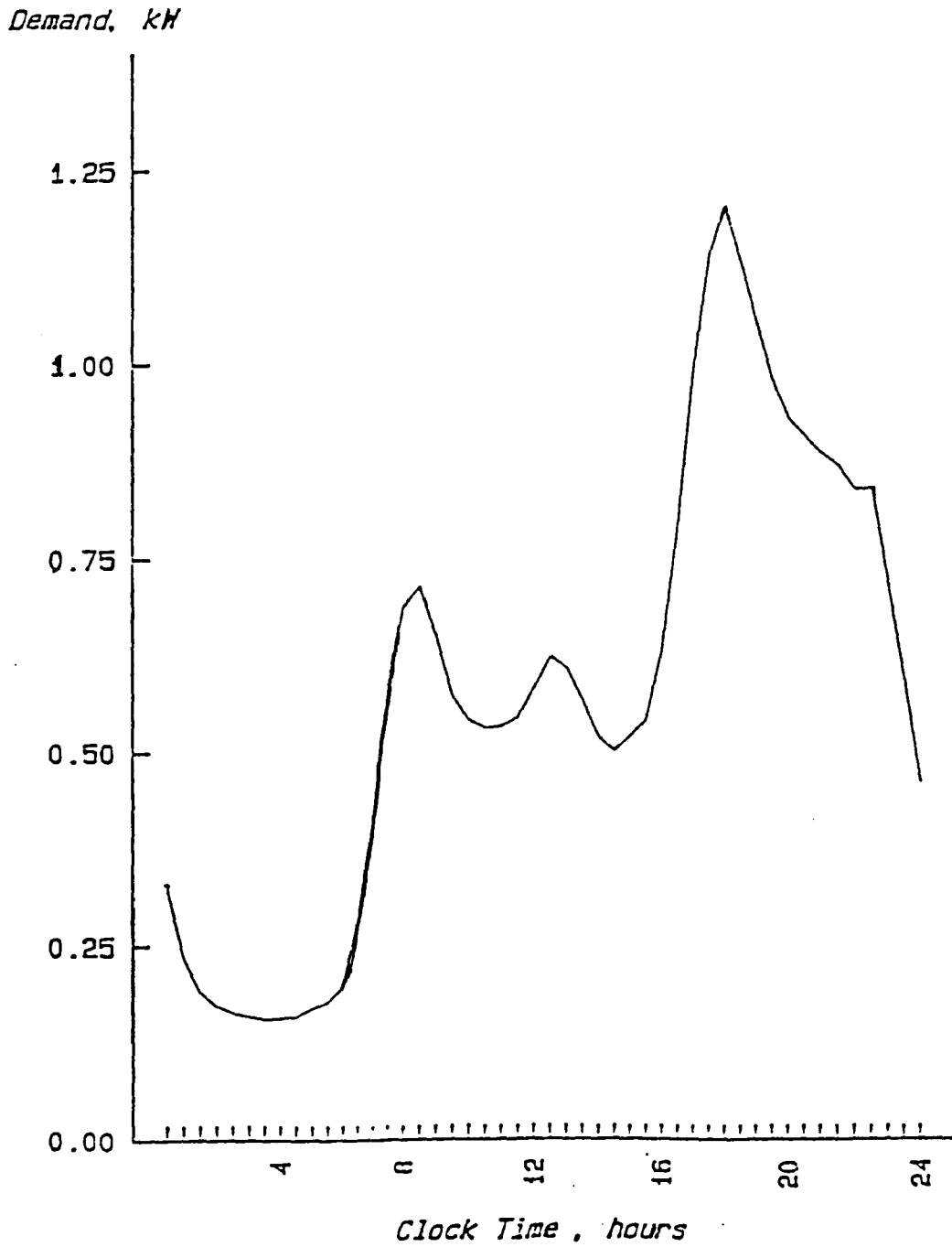


Figure 4.3 Typical Load Shape for Domestic Demand

Commercial water-heating load;

and residuals.

4.3.1 Representation of the components

Figures 4.1, 4.2 and 4.3 show the average industrial, commercial and domestic demands on weekdays [221, 218, 223]. These types of curves can be represented using mathematical expressions.

The following five basic curves have been suggested representing the complex components:

1) Constant curve

Constant curve is defined in the form of a list:

$$[\text{const } h \ t_1 \ t_2]$$

where **const** indicates the curve is a constant with a height of **h** and duration from t_1 to t_2 .

2) Ramp curve

Ramp curve is defined in the form:

$$[\text{ramp } \alpha \ t_1 \ t_2]$$

which indicates a ramp curve with a slope of α from t_1 to t_2 .

3) Normal distribution

Normal distribution is defined as:

$$[\text{norm } h \ t \ \sigma]$$

which has the peak value of h at time t with spread indicator of σ .

4) Positive part of normal distribution:

Defined as:

$$[\text{posnorm } h \ t \ \sigma]$$

which indicates the left half part of a normal distribution curve.

5) Negative part of normal distribution:

Defined in the same way as **posnom** curve:

$$[\text{negnorm } h \ t \ \sigma]$$

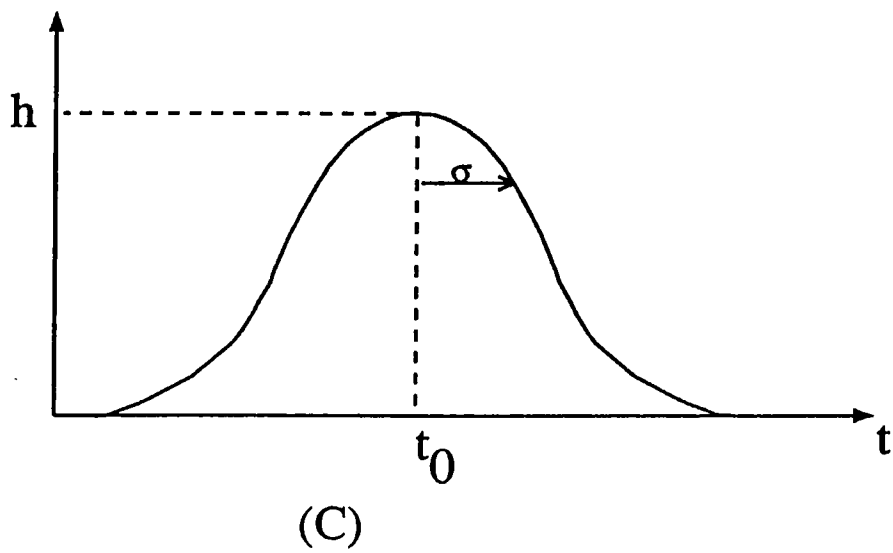
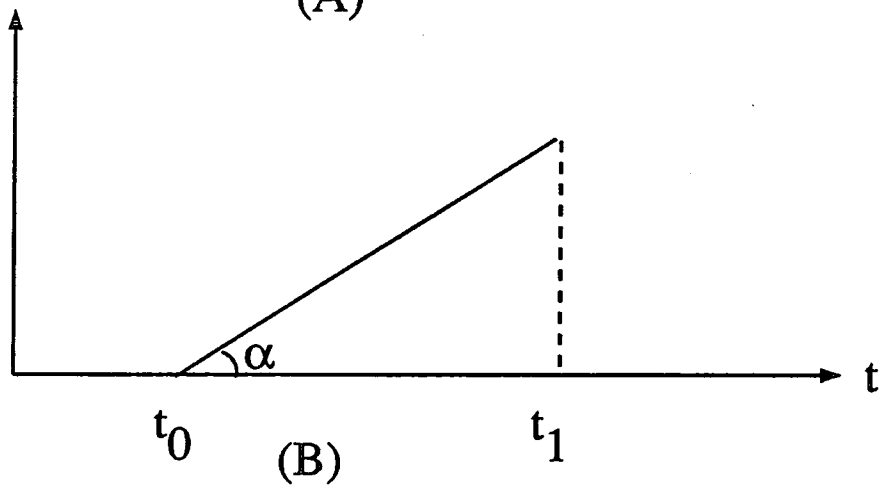
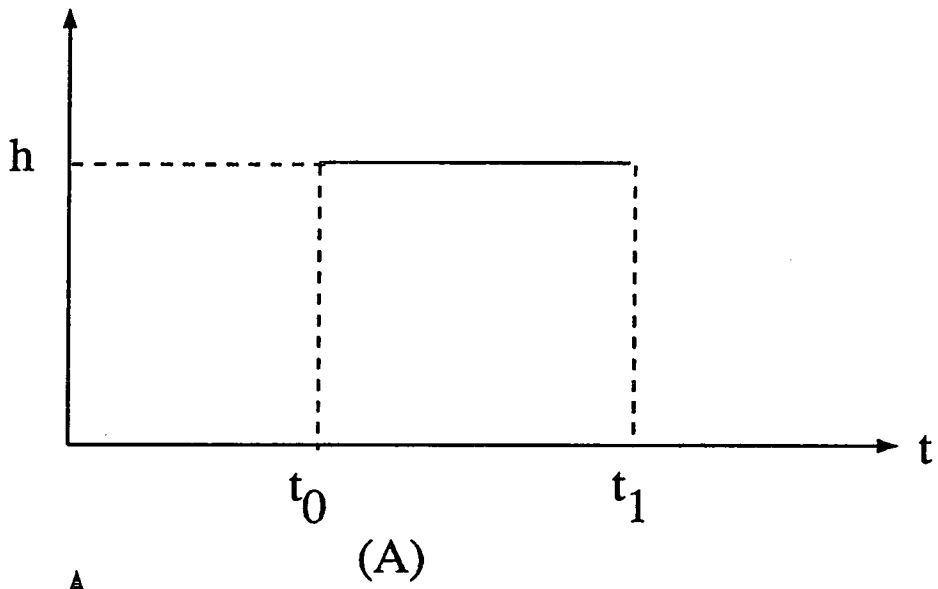
which represents the right half part of a normal distribution curve.

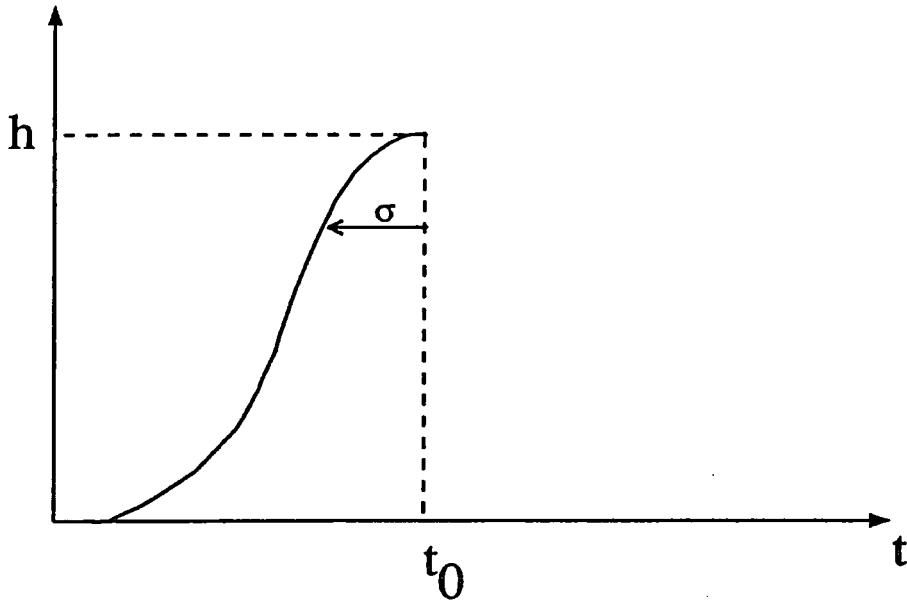
These five basic curves are shown in Figure 4.4.

4.3.2 Expression of components using the basic curves

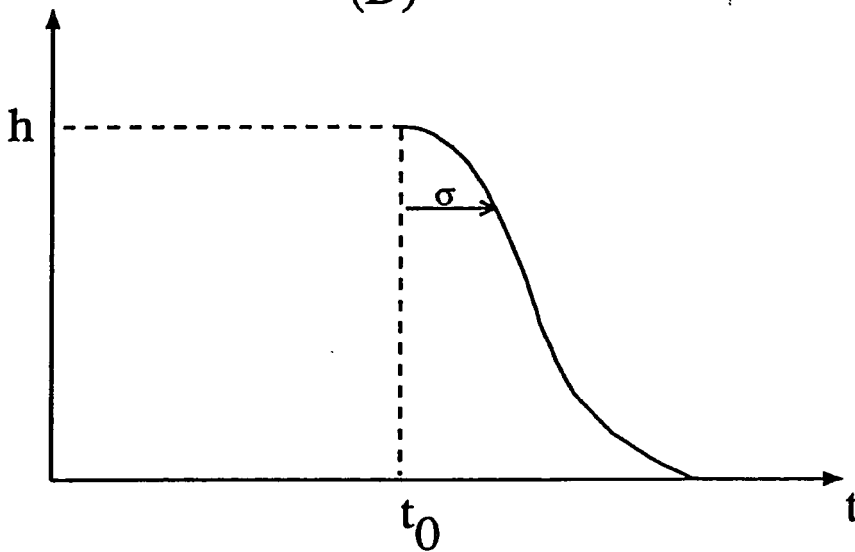
Based on existing knowledge and operator's experience, load shapes of different components can be simply modelled and expressed as following:

Industrial base load:





(D)



(E)

A: Constant curve;

D: Pos-norm curve;

B: Ramp curve;

E: Neg-norm curve.

C: Norm curve;

Figure 4.4 Five Basic Curves

```

[[const 0.5 1 288]
[posnorm 0.3 96 4]
[const 0.3 96.1 192]
[negnorm 0.3 192.1 4]]*

```

which shows that the industrial load starts to increase in the morning and decrease from late afternoon. This is a typical two-shift industrial load. Three-shift loads are included in the "const" part of the expression.

Industrial lighting and heating loads are not greatly affected by weather conditions, thus, they can be included in the above industrial load in the process of disaggregation.

Domestic lighting load:

```

[[const 0.2 1 288]
[posnorm 1.0 6 4]
[const 1.0 6.1 36]
[negnorm 1.0 36.1 4]
[norm 0.5 72 6]
[posnorm 1.2 216 4]
[const 1.2 216.1 272]
[negnorm 1.2 272.1 4]]

```

This represents part of the curve in Figure 4.3. There is a peak load around breakfast time for the domestic lighting load. During the day time, the domestic lighting load is relatively low. In the evening, it starts to increase and reaches another peak and then starts to drop gradually from midnight.

Domestic automatic space-heating load:

```

[[const 0.5 0.1 288]

```

* time and period are presented in the expression of lists by slots: 1 slot = 5 minutes.

[posnorm 0.3 1 3]
[const 0.3 1.1 36]
[negnorm 0.3 36.1 4]
[norm 0.5 45 6]
[posnorm 1.0 216 4]
[const 1.0 216.1 272]
[negnorm 1.0 272.1 4]]

Generally speaking, this is the automatic space heating load in winter, which behaves similarly to the lighting load.

Domestic human space-heating load:

[[norm 0.5 48 6]
[norm 1.0 220 12]]

This part is consumed by the switching on of heaters by residents.

Domestic automatic water-heating load:

[[posnorm 0.5 0.1 4]
[const 0.5 0.2 84]
[negnorm 0.5 84.1 4]]

This load is relatively similar to the space heating load.

Domestic human water-heating load:

[[norm 0.25 78 6]
[norm 0.5 240 12]]

This load is more or less the same as the space heating load.

Domestic cooking load:

[[norm 1.0 84 6]
[norm 0.8 150 9]
[norm 1.2 240 12]]

This load is consumed around three-meal times.

Tea-coffee break load:

[[norm 0.5 126 6]
[norm 0.5 180 12]]

The domestic loads for entertainment can be included in the lighting and heating load, because they are consumed mostly in the evening together with lighting and heating load. The loads consumed by refrigerators are relatively small, and constant over 24 hours, although there are some variations with temperature changes. So, they can be left in the residuals. The other domestic loads such as clothes washing and drying loads are usually consumed on weekends. They are small and irregular on weekdays. So, they are also left in the residuals.

Commercial lighting load:

[[posnorm 0.5 96 4]
[const 0.5 96.1 204]
[negnorm 0.5 204.1 4]]

This commercial lighting load is used around office working hours.

Commercial automatic space-heating load:

[[posnorm 0.5 96 4]
[const 0.5 96.1 204]
[negnorm 0.5 204.1 4]]

This part is also similar to the lighting load.

Commercial human space-heating load:

[[posnorm 0.3 96 9]]

This is extra part of the automatic heating load when work is started.

Commercial automatic water-heating load:

[[posnorm 0.5 0.1 4]

[[norm 0.5 0.2 84]

[negnorm 0.5 84.1 4]]

This part is similar to the lighting load.

Street lighting load:

[[posnorm 0.5 0.1 4]

[const 0.5 0.2 44]

[negnorm 0.5 44.1 4]

[posnorm 0.5 210 4]

[const 0.5 210.1 287.9]

[negnorm 0.5 288 4]]

This load represents the lighting load affected by sunset and sunrise time.

4.4 Summation of the components into the overall load

The shape of each component has been defined by expressions as above. How do they co-ordinate to form the overall load? In other words, what is the weighting factor of each component comprising the overall load?



Supposing weighting factors for the different components are S_1, S_2, \dots, S_n , they can usually be estimated by applying a linear regression method:

$$L(t) = X_1(t) * S_1 + X_2(t) * S_2 + \dots + X_n(t) * S_n$$

where $X_i(t)$ and S_i are the load at time t and weighting factor of i th component respectively.

Obviously, this formula should be applied over a period of 24 hours ($t=1, 2, \dots, 48$). However, when it is applied to the recorded load data of the CEGB system, it is found that the weighting factors S_i are far from satisfaction: some weights are negative. This is obviously not realistic. The reason is that not all of the components have been well expressed by the five basic curves. There are still a lot of trivial loads not included, for they occupy only a small amount among the overall load, compared with the industrial, domestic and commercial loads already defined.

The problem now becomes one of how to fit the components to the actual load data and estimate their weights. The following sections present a new approach to solve the problem.

4.5 Objective functions

In order to derive a best fit for the overall load, we need to define the objective function. The initially defined curves do not provide a satisfactory result immediately, and it is therefore necessary to adjust the curves in order to minimise some cost functions, such as:

1) to reduce the difference between the maximum and minimum of the residuals:

$$\text{Minimise } (\max(\text{residuals}) - \min(\text{residuals}))$$

This objective is used to model load components during day time.

2) to minimise the maximum of residual loas:

Minimise (max(residuals))

This objective is used to model all the loads over 24 hours.

In order to achieve the objective functions, the general procedure is conducted as follows:

- 1) to find t_{max} which indicates the location of max(residuals);
- 2) to modify **pos-neg** curves;
- 3) to modify **norm** curves.

The three steps are taken recursively until the objectices are met.

4.6 Fitting of the components

In order to fit each component to the overall load data, weights (or base loads) for different components are to be found, and the various curves can be modified.

•

4.6.1 Estimation of weight for each component

Before each base load is obtained accurately, an initial small value (e.g., 1000 MW) is assigned to each component according to its relative weight in the overall load. Since the weight of industrial load is much higher than any other component, it can be given comparatively large initial value.

The weights S_i can be adjusted (increased) in order that the difference between the actual load and sum of the estimated components is minimised. At the same time, the defined component curves can also be modified, since the initial expression is only approximate.

4.6.2 Curve modification method

For each basic curve, there are three parameters to define it. For example, the three parameters of a normal distribution curve are: its height, location, and its spread. Although all of them are equally important in defining the curve, it is necessary to order them in the following way according to their relative importance for the overall load.

From the expression of the components defined earlier, it is seen that the normal distribution curve and the posnorm-constant-negnorm curve are the most concerned. We will analyse how to modify these two kinds of curve shapes in order to fit the components to the overall load.

4.6.2.1 Changing normal curves

For a normal distribution curve of the form:

$$[\text{norm } h \ t \ \sigma]$$

Three parameters are:

- a) the height h .
- b) the location t ;
- c) the spread σ .

The parameters can be adjusted in turn in the following order:

- a) the location t ;
- b) the spread σ ;
- c) the height h .

They are changed in the following way:

- a) to move the location of t

If the objective function has a maximum value at time t_{max} we can move its location t_0 towards t_{max} , until the objective function is locally minimised.

b) to change the spread σ

Since an approximate normal distribution curve spreads from $t_0 - 2 * \sigma$ to $t_0 + 2 * \sigma$, the spread of σ is widened, until the objective function is locally minimised, if time t_{max} is located between $t_0 - 2 * \sigma$ and $t_0 + 2 * \sigma$.

c) to magnify the height of h

Finally, the error can be minimised by increasing the height of h .

4.6.2.2 Changing pos-neg curves

The change of a **pos-neg** curve is more or less the same as that of the **norm** curve. Suppose the **pos-neg** curve is in the form:

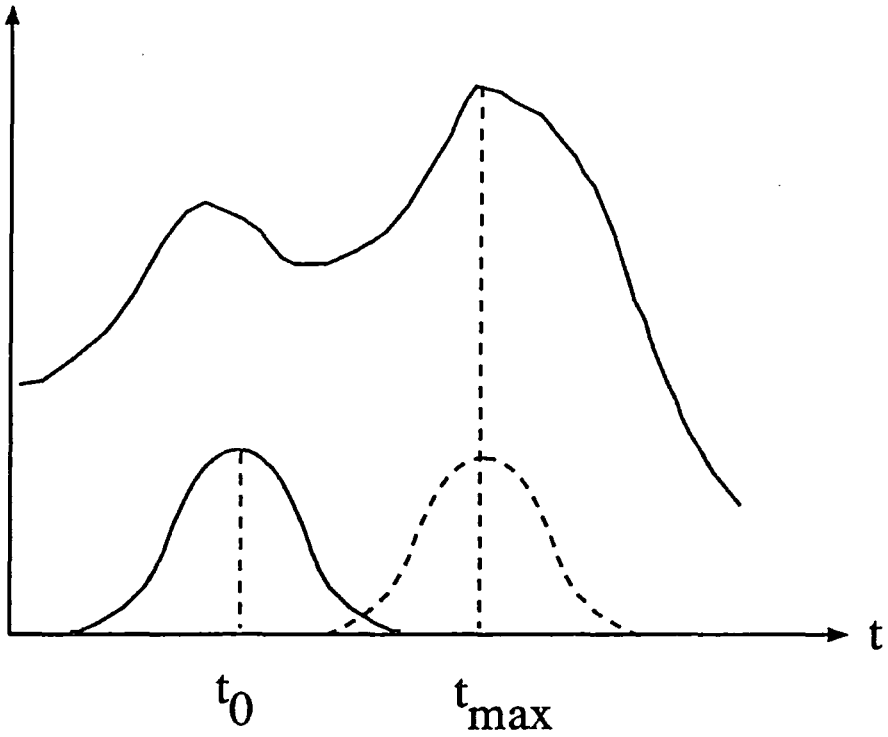
$$[[\text{posnorm } h \ t_1 \ \sigma_1][\text{const } h \ t_1 \ t_2][\text{negnorm } h \ t_2 \ \sigma_2]]$$

Although there are 9 coefficients in the expression, there are in fact only 5 independent parameters in the expression:

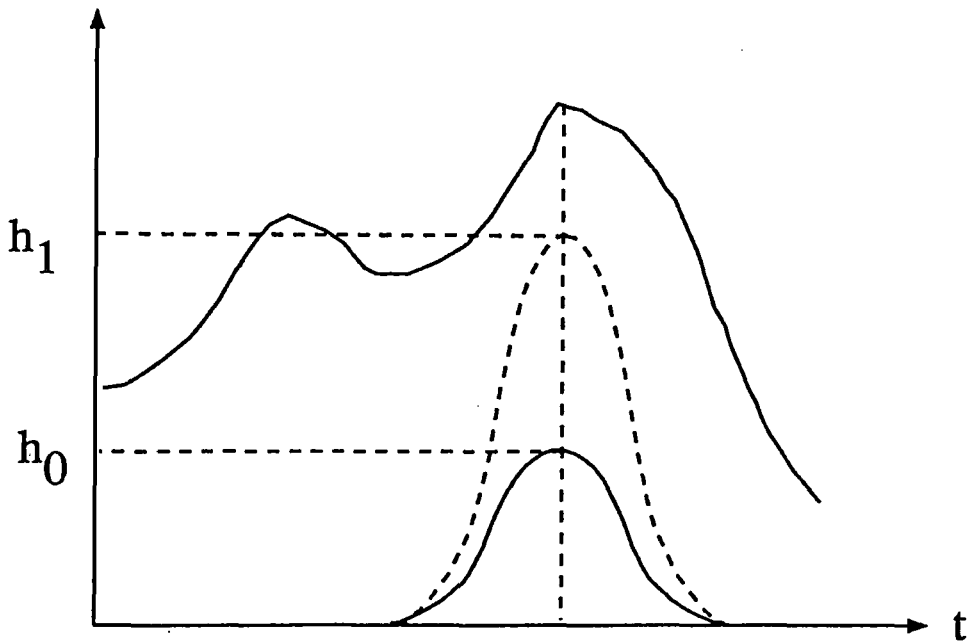
- a) the height h ;
- b) the location t_1, t_2 ;
- c) the spread σ_1, σ_2 .

Similarly to the modification of a **norm** curve, these parameters are changed in the following order:

- a) the location t_1, t_2 ;
- b) the spread σ_1, σ_2 ;



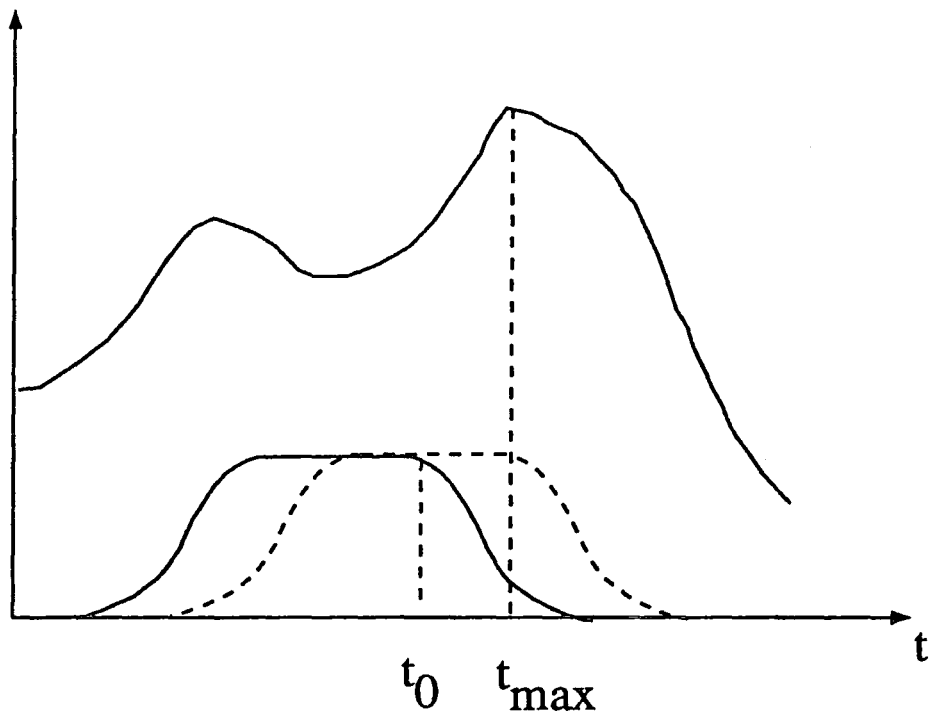
(A)



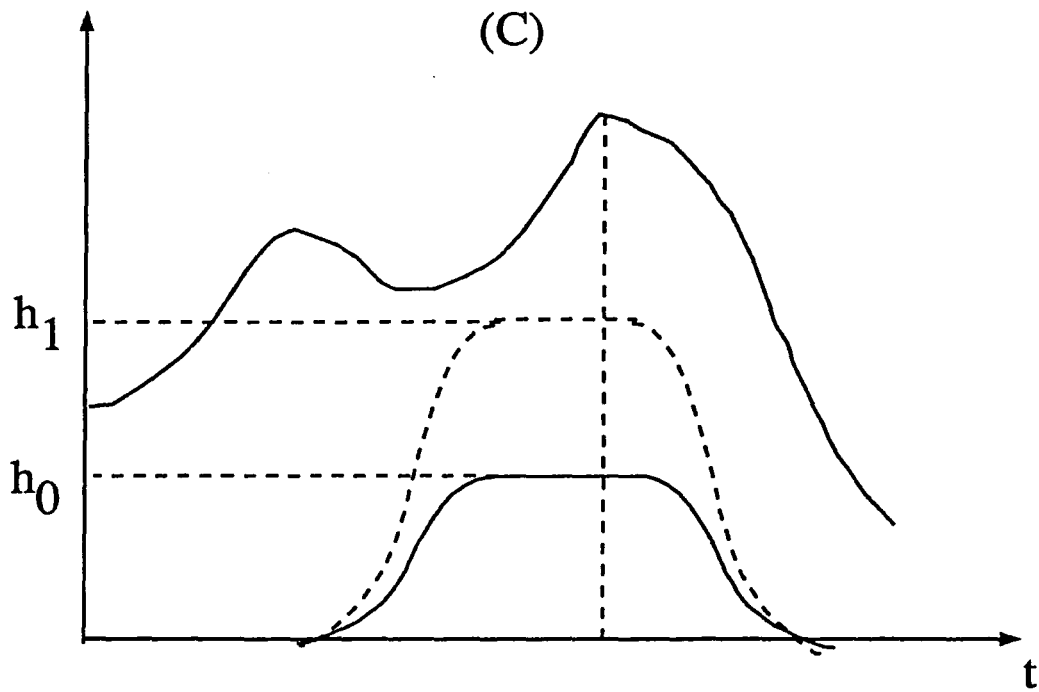
(B)

(A) Moving location t_0 of norm curve;

(B) Magnifying height h_0 of norm curve;



(C)



(D)

- (C) Moving location t_0 of pos-neg curve;
- (D) Magnifying height h_0 of pos-neg curve;

Figure 4.5 Modification of Curves

c) the height h .

They are adjusted in the following way so that the objective functions can be achieved.

a) to move the location of t_1, t_2

Parameters t_1 and t_2 can be modified only when the maximum error is at t_{max} which is between $t_1 - 2 * \sigma_1$ to t_1 or between t_2 to $t_2 + 2 * \sigma_2$.

b) to change the spread σ_1, σ_2

After t_1 and t_2 are determined, similarly, σ_1 and σ_2 can be widened if the maximum error is at t_{max} which is outside (t_1, t_2) .

c) to magnify the height h

Thirdly, by increasing the height h , we can minimise the error if time t_{max} is located between $t_1 - 2 * \sigma_1$ and $t_2 + 2 * \sigma_2$.

The modification of the curves is illustrated in Figure 4.5.

4.6.3 Sequence of modifications

In the process of increasing base load and curve modification, the problem of change orders must be considered.

4.6.3.1 Order of changing components

After an initial assignment of base load to each component, each base load can be increased in order to reduce the residual between the overall load and the sum of components. Any base load could be chosen to be increased. However, priority is given in order, according to the relative weight in the

overall load. For example, base load of the industrial sector has the priority to increase over the others.

4.6.3.2 Order of changing basic curves

Generally speaking, since the **pos-neg** curves cover a longer duration of time than a single **norm** curve, we place the priority of curve changing in this way:

pos-neg > norm.

If there are several **pos-neg** curves that can be modified to minimise the error, for the same reason, the one with the longest spread time should be modified first. The same principle is applied for **norm** curves.

The curves are changed generally according to the above order. However, some obvious constraints, such as the occurrence times of components, can be applied to the modification in the form of production rules.

The detailed procedures written in POP-11 are listed in appendix 3.

4.7 Results

The proposed algorithm was tested using the CEGB system load data of 1/2/1984 and 6/6/1984. The results are shown in Table 4.2 where “Decompose 1” and “Decompose 2” indicate minimising the first and second objective function respectively.

Figures 4.6 and 4.8 depict the residuals and the overall loads, where “RES 1” and “RES 2” indicate minimising the first and second objective respectively. The dashed curves (in Figures 4.6 and 4.8) are quite flat, which means the load consumed between the peak and trough time has been well-modelled. The residuals (the dotted curves) are relatively small, which means most of the loads have been included in the components. It can be seen from both figures that

both peak and trough loads have been disaggregated both in summer and winter. Figures 4.7 and 4.8 compare the summation of disaggregated components with the overall loads. It can be seen that the curves of summation of disaggregated components are different in winter and in summer, since the patterns of the overall load curves are different. For the winter load (Figure 4.7), the evening load is generally modelled. But there is much difference during the day time, simply because of the mis-modelling of lighting and heating loads. The difference around the time immediately after midnight can be removed if the heating load can be correctly modelled for the "economy 7" load. For the summer load (Figure 4.9), similarly, there is a deviation of loads around midnight. Moreover, the evening peak load is not fitted very well. Generally speaking, however, both objectives have been reached. Although there are no appropriate data to validate each of the components, the disaggregation is based on the knowledge of characteristics of the load components.

Table 4.2 Residuals of Disaggregated Load

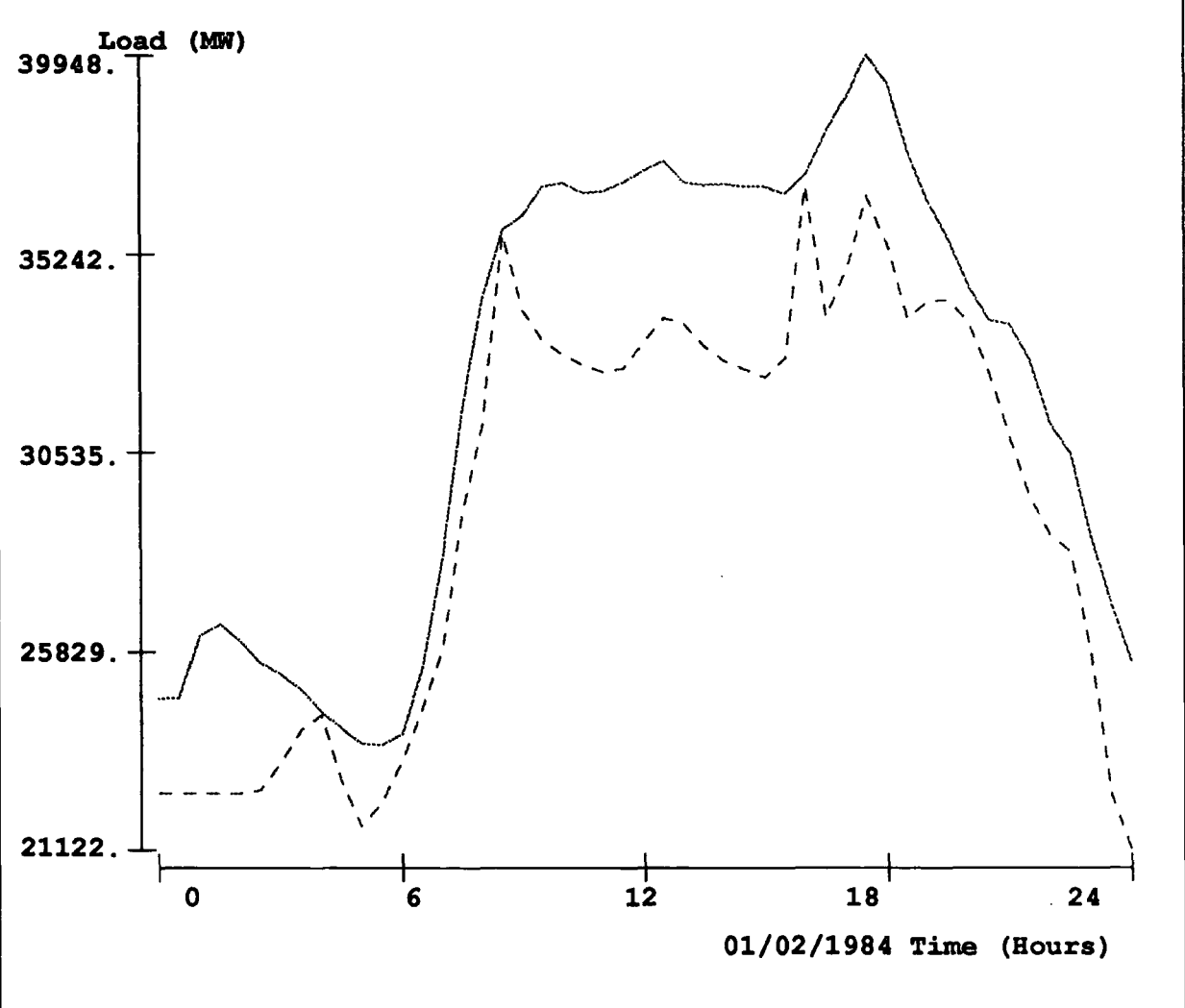
	01/02/1984			
	Max.		Min.	
	Residual(MW)	Time	Residual(MW)	Time
Original	39,948	17:00	23,602	5:30
Decompose 1	9,753	8:00	6,440	8:30
Decompose 2	4,563	23:30	98	4:00
	06/06/1984			
	Max.		Min.	
	Residual(MW)	Time	Residual(MW)	Time
Original	28,996	9:00	16,214	4:00
Decompose 1	6,358	18:30	2,532	20:00
Decompose 2	2,767	21:30	102	17:00

TITLE: Load Disaggregation

FIGURE: Overall Load & Summation of Components (01/02/1984)

----- ACT

----- SUM

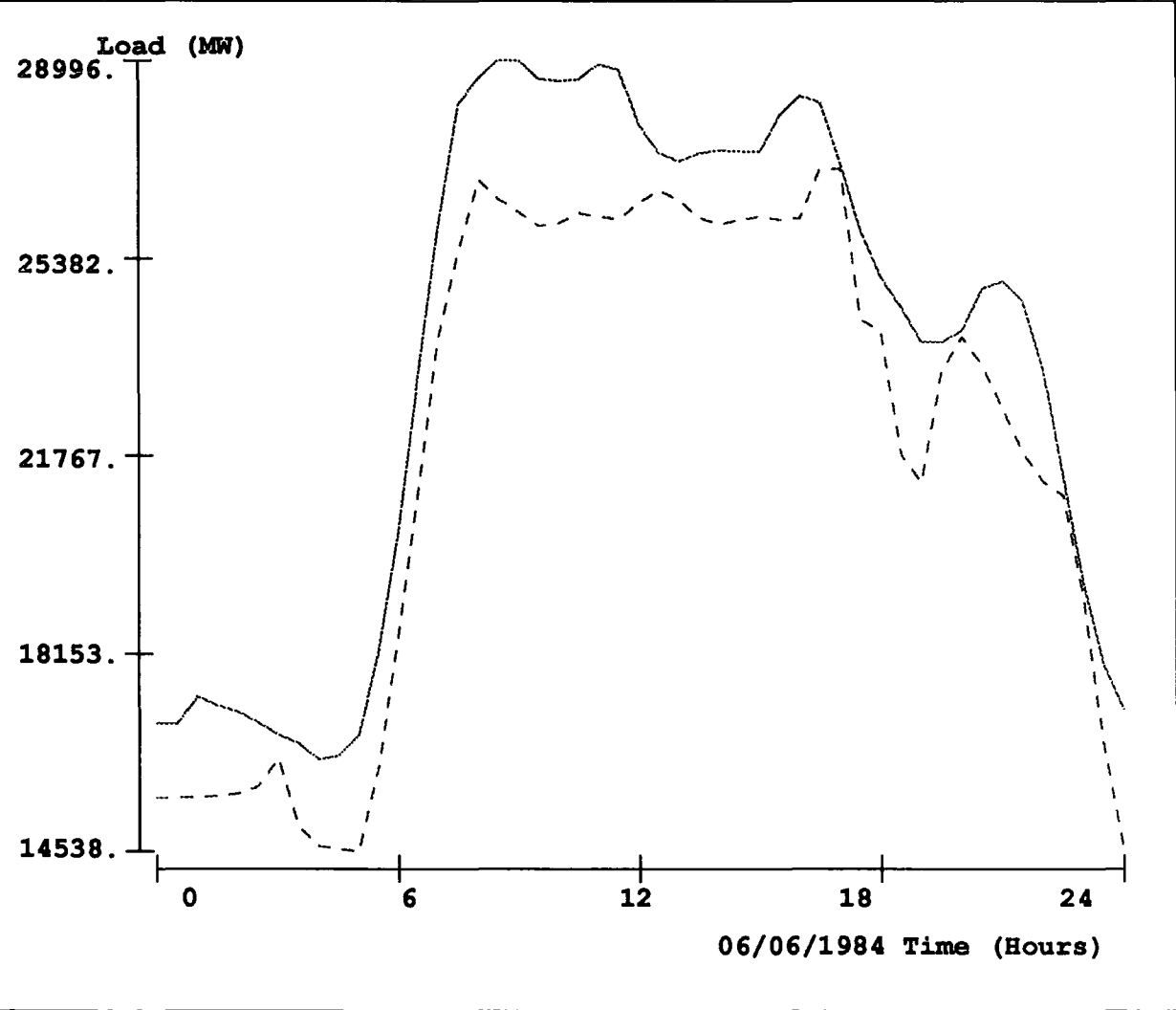


**Figure 4.7 Actual Load and Summation of Components
for Winter Weekday (01/02/1984)**

TITLE: Load Disaggregation

FIGURE: Overall Load & Summation of Components (06/06/1984)

— ACT
- - - SUM



**Figure 4.9 Actual Load and Summation of Components
for Summer Weekday (06/06/1984)**

4.8 Summary

Since the overall electrical demand is the sum of electricity consumed by each electric appliance in a power system, it is affected by many different factors. In order to obtain a good predictor, relationships between the composition of the overall load and the causal factors must be found. Implementation of load management makes electricity utilisation behaviour different from what it was. So, it is necessary to break the overall load into its components. After each demand of the composite is forecast, the overall load can be estimated “bottom-up”.

Usually, the overall load can be categorized as: industrial, commercial, and domestic loads. According to the different end usage, each load can be further disaggregated into its own composites. For example, domestic loads consist of domestic heating load, domestic cooking load, etc..

Usually, there are two approaches to disaggregate the overall load: surveying and by heuristic methods. This chapter applies the latter one.

Much effort has been devoted in this chapter to the definition and representation of each component, which is based on the adequate understanding of the characteristics of each class of load. The representation is constructed from the mathematical function of normal distribution and constant curves. Since the initial representation of each component was not perfect in fitting the overall load, it is essential to change the shapes and weights of the components in order to make up the overall load.

Although there are not appropriate end-use data to validate the results of disaggregation, the residuals of the tests are relatively small. This means that the overall load can be broken into its composites. The next chapter will be devoted to load prediction around time change-overs (both from Greenwich Mean time to British Summer time and vice versa) based on the disaggregation technique proposed in this chapter.

CHAPTER 5

LOAD PREDICTION OVER TIME CHANGE-OVERS

5.1 Introduction

One problem in short-term demand prediction is to cope with the time change-over from Greenwich Mean Time (GMT) to British Summer Time (BST), and vice versa.

BST starts from the last Sunday in March and ends on the fourth Saturday in October. This involves setting the clock forward by one hour from GMT and hence causes the discontinuity of load data being stored. This is to say that, when the time system alters from GMT to BST, there will be a gap of load data for one hour, whereas when the time is changed from BST back to GMT, there will be one hour extra of data recorded. As a solution to this problem, the CEGB uses the Dispatch Project computer to store load data time-stamped by GMT all the time [27]. By this means, the load record time would be monotonically increasing, load data would not have to be thrown away at the end of the BST period, and no extra data would be added at the start of BST. The problem which remains, however, is that the change-over alters the consumer's use of electrical power, since some loads which are regulated by nominal clock time are shifted at the change-overs, while those which are governed by independent factors, such as off-peak time-switches and the onset of darkness, are not.

During the period of time change-overs, load patterns change from week to week, even for the same days-of-week. And the effect of change-overs on loads does not simply shift their loads forward or backward by one hour. This makes the conventional time series method extremely difficult to predict future loads

in the short term. However, the time change-over affects the load behaviour in the same way from year to year, which enables load prediction easier if the historical loads, of as far as previous years, are available. So, when prediction is being made around the periods of time change-overs, the procedures which are suitable for prediction over this period should be adopted while the conventional time series method remains for use for the normal periods.

This chapter proposes an approach to conduct prediction of load around time change-overs. The approach is based on the disaggregation method proposed in chapter 4. First, section 5.2 illustrates the load characteristics around time change-overs, both from GMT to BST and from BST to GMT. The problems of conventional time series method encountered for short-term prediction over these periods are explained in section 5.3. Following the analysis of the characteristics, section 5.4 introduces the adoption of relative gaps the concepts of which have been widely applied to predicting loads for special events. Section 5.5 presents a new approach which uses both weather information which indicates the effect of time change-overs on demand, and recent loads to predict the load behaviours after time change-overs. In this section, changes of time from GMT to BST and from BST to GMT are separately considered, but in a similar way. The approach predicts the overall load by separately forecasting two parts: lighting load and the rest. Section 5.6 lists some knowledge stored in knowledge base which is used by the approach. Next, section 5.7 assesses all these approaches. Finally, discussion and conclusion are given in the last section.

5.2 Load characteristics around time change-overs

By investigating the demand record (time-stamped by GMT) of two weeks over the period of change-over (one week before the change, the other after the change) from GMT to BST, it is found that the load patterns change greatly (see Figure 5.1). It is noted in this figure that the overall load was lower, moving forward from the morning on and having a rather significant trough before the evening peak, as compared with that of the same day-of-week in the previous week before the time change-over. But when the time changed

TITLE: Load Characteristics

FIGURE: Effects of Time Change-overs (GMT -- BST)

—— GMT_83.P; ····· GMT_84.P;
- - - - BST_83.P; ····· BST_84.P;

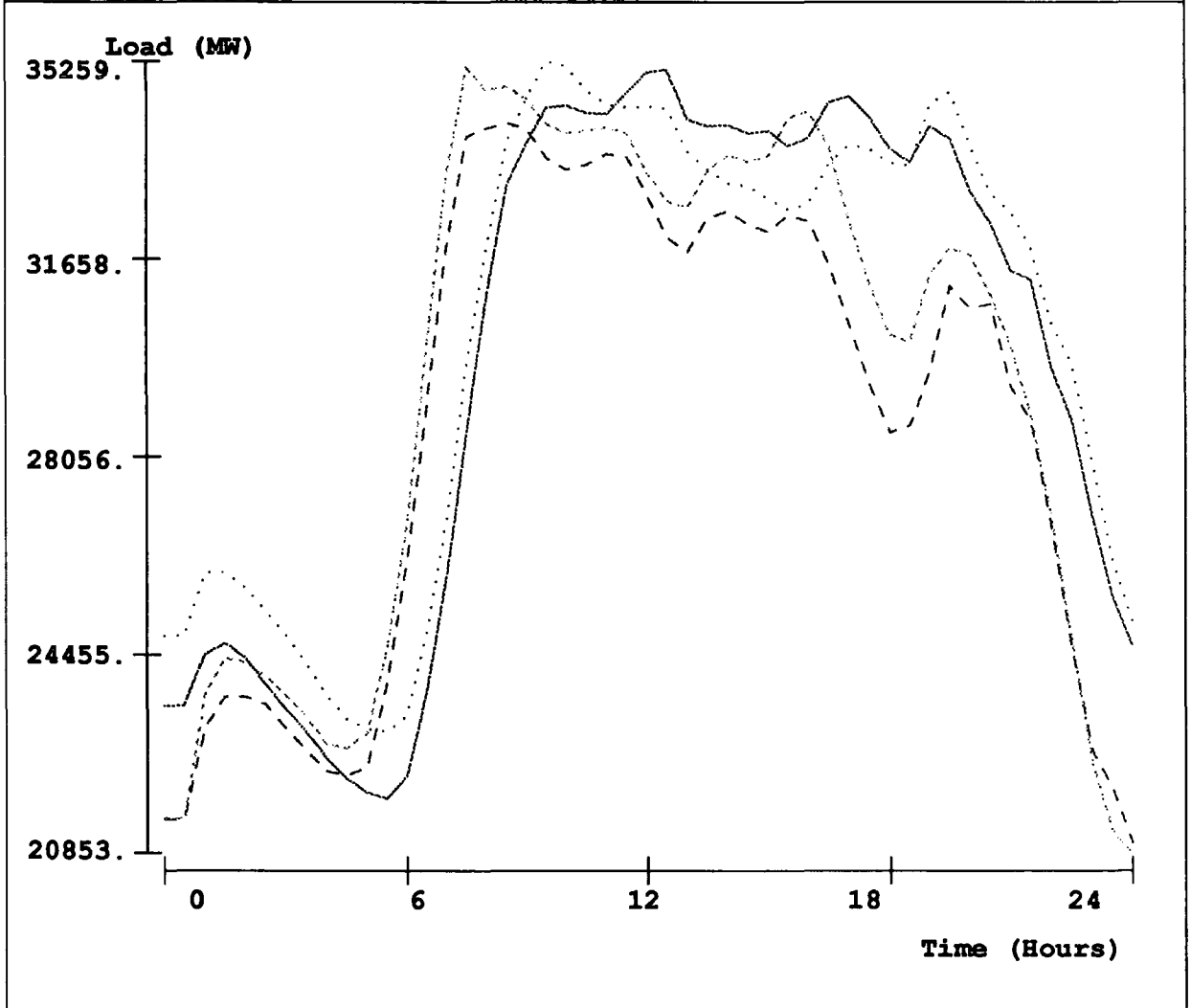


Figure 5.1 Effects of Time Change-overs on Load (GMT - BST)

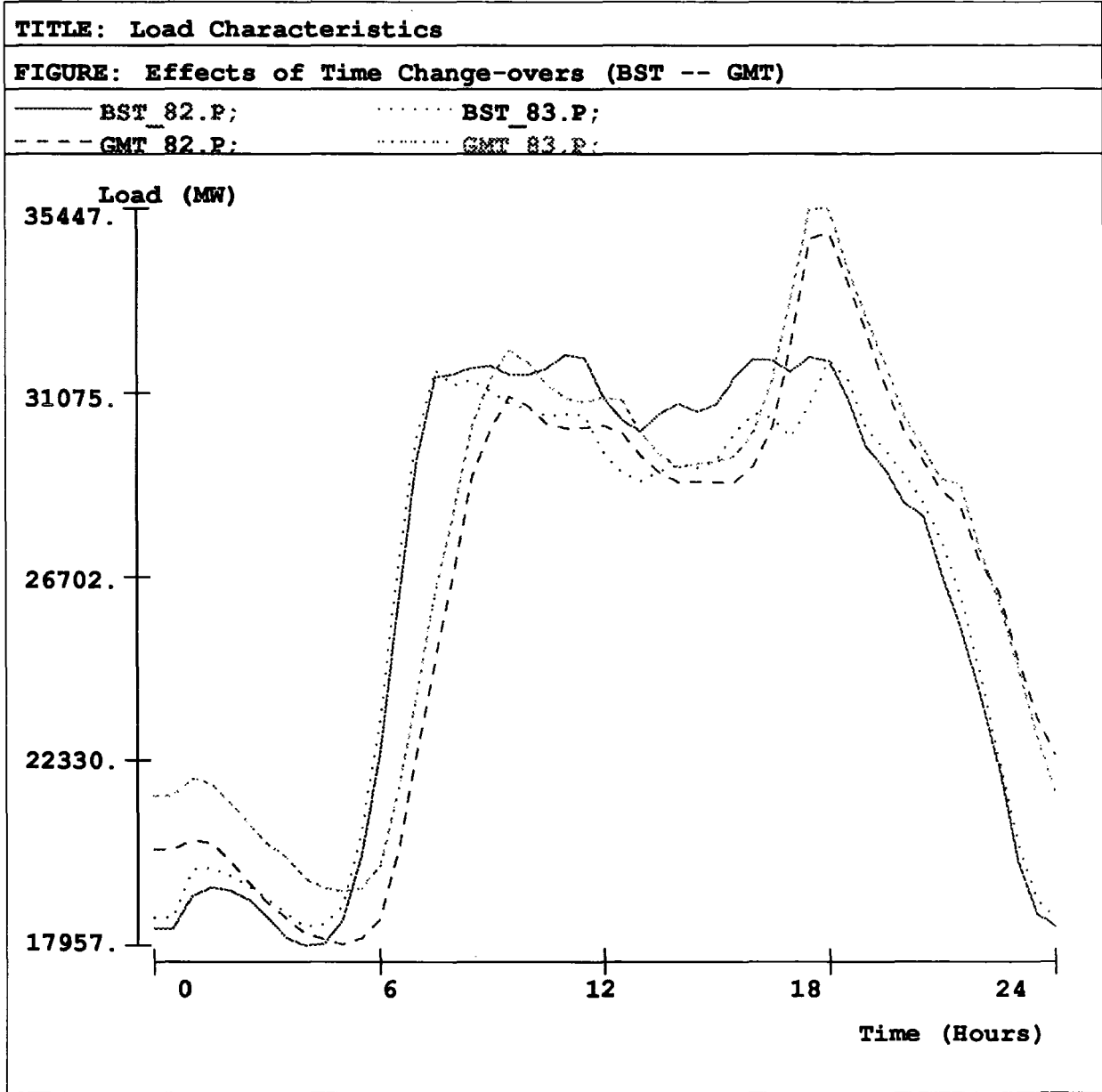


Figure 5.2 Effects of Time Change-overs on Load (BST - GMT)

from BST to GMT, the overall load shifted backward from the morning on, with a more considerable evening peak, while compared with that before the time change-over (see Figure 5.2).

Both figures show that the morning load altered and end-of-the-working-day peak load was affected by the change-over.

5.2.1 From GMT to BST

Comparing the daily load profile of one week before the time change with that of the week after the change, it is found that the overall load was lower, and shifted forward from the morning on, and a noticeable trough appeared before the evening peak. This could be explained as follows:

After the time changed to BST, daily activities, such as industrial, commercial and domestic, alter by one hour to follow the time system. So, the morning loads start to increase one hour earlier than under GMT. The overall load around day time in BST was less than that in GMT, which was caused by the reduced heating load due to the warmer weather. The trough before the evening peak was due to the fact that most of the day activities had finished, but the domestic lighting load was not on by that time, because of later sunset.

5.2.2 From BST to GMT

Comparing the load of one week before the time change-over with that after the time changing, on the contrary, it is seen that the overall load has moved forward from the time of the first trough happening before the sunrise, and there was a significant peak around sunset. This is because the initial peak before the first trough resulted from the activities of the previous day, which was not affected by the lighting load altered by the time system. From the first trough onwards, the load moved by one hour mainly due to the changed time. The tremendous peak existing around sunset is due to the fact that the

day activities have not yet finished by that time because of the one hour delay, and the lighting load is on due to the earlier sunset.

5.3 Prediction by ARIMA

Certainly for this kind of load characteristics, the conventional ARIMA model can not predict accurately in short period. Tables 5.1 and 5.2 list the prediction results against the CEGB system load around time change-overs made from the ARIMA model of $(1,0,1)_1 \times (1,0,1)_{48} \times (0,1,1)_{336}$.

**Table 5.1: Load Prediction Around Time Change-over by ARIMA
(GMT → BST)**

Date	Day-of-week	Original ARIMA (%)	
		R.M.S.	Max.
26/3/1984	Monday	10.03	-27.67
27/3/1984	Tuesday	10.86	24.95
28/3/1984	Wednesday	10.67	-23.67
29/3/1984	Thursday	10.89	-24.55
30/3/1984	Friday	11.01	-23.54

**Table 5.2: Load Prediction Around Time Change-over by ARIMA
(BST → GMT)**

Date	Day-of-week	Original ARIMA (%)	
		R.M.S.	Max.
29/10/1984	Monday	10.46	-31.95
30/10/1984	Tuesday	10.39	30.48
31/10/1984	Wednesday	11.80	32.42
1/11/1984	Thursday	11.84	33.67
2/11/1984	Friday	11.73	34.99

From these two tables, it is seen that the errors are extremely large and the results can not be accepted by on-line operation. It can be concluded that the conventional ARIMA model can not predict the load change caused by the time change-overs.

Figures 5.3 to 5.7 show the difference between the actual recorded loads and the predicted loads made from the ARIMA model for the weekdays of first week following the time change-over (from GMT to BST) while Figures 5.8 to 5.12 illustrate the results of that from BST to GMT. It can be seen from the figures that the load patterns predicted by the ARIMA model remains similar to what they were before time change-overs. Even though the influenced loads such as that of Monday and Tuesday are used in the parameter estimation, the predictions for Wednesday, Thursday, and Friday do not show any improvement. One of the important reasons is that the model needs a long period of time to habituate to the new load pattern, and the past load data exhibit more strong weekly cycles than daily cycles.

From the load profiles shown in the figures 5.3 to 5.12, it can also be concluded that we could not simply shift the predicted load profiles which are obtained from the ARIMA model by one hour as the loads after the change-overs. Therefore, short-term prediction around time change-overs can not be made by the ARIMA model. Either enough past load data which reveal the similar effect of time change-over are available, or more information which indicates the utilisation of electricity is obtained, then the problem can be solved.

A close inspection of Figures 5.1 and 5.2 indicates that time change-overs have similar effects on the load changes in successive years. It can be derived from this fact that load prediction can be made on the basis of historical load of previous years.

TITLE: Prediction Around Time Change-overs (GMT -- BST)

FIGURE: For Monday by ARIMA

— Prediction
- - - Act

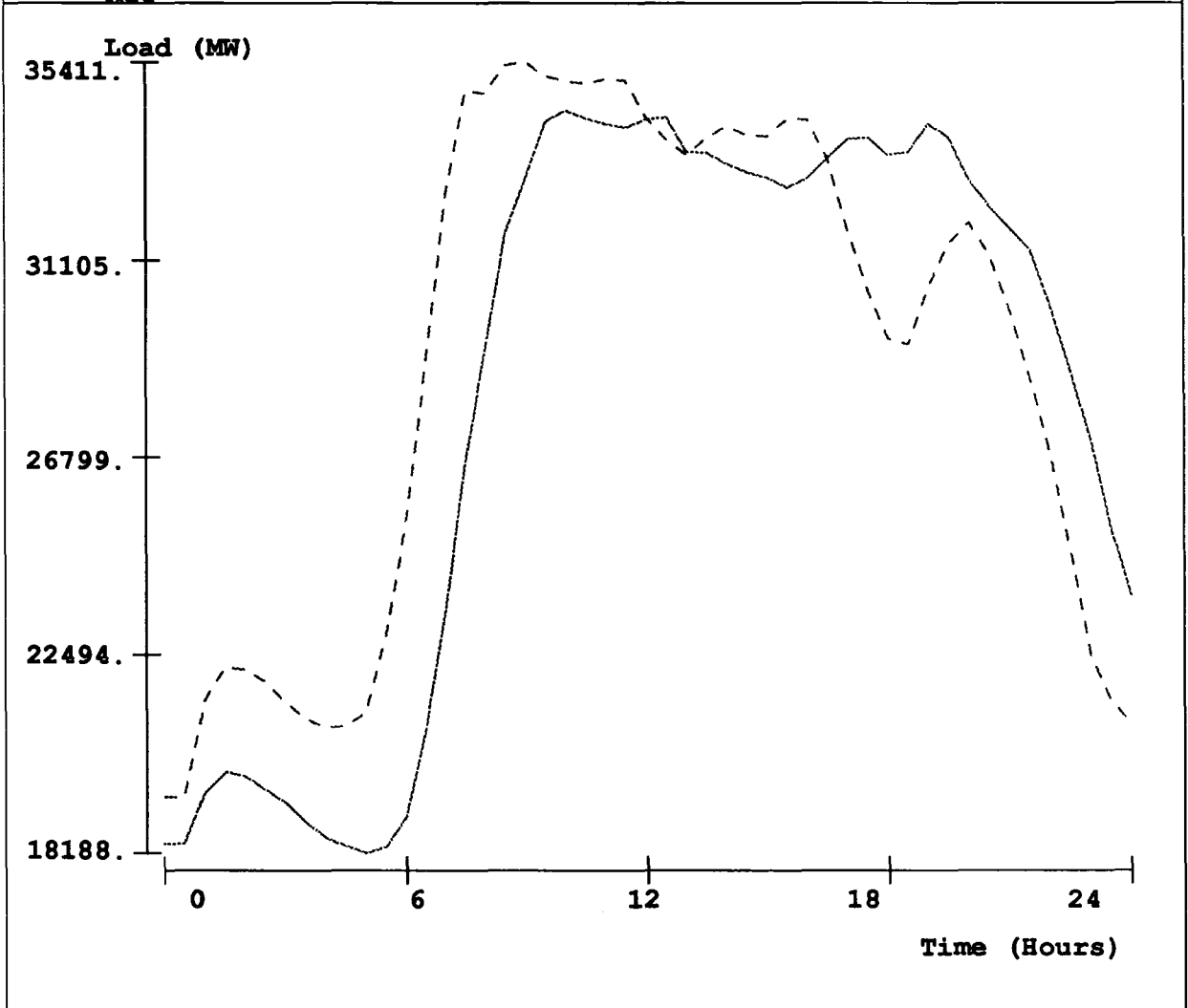


Figure 5.3 Prediction of GMT/BST Effects for Monday by ARIMA

TITLE: Prediction Around Time Change-overs (GMT -- BST)

FIGURE: For Tuesday by ARIMA

— Prediction

- - - Act

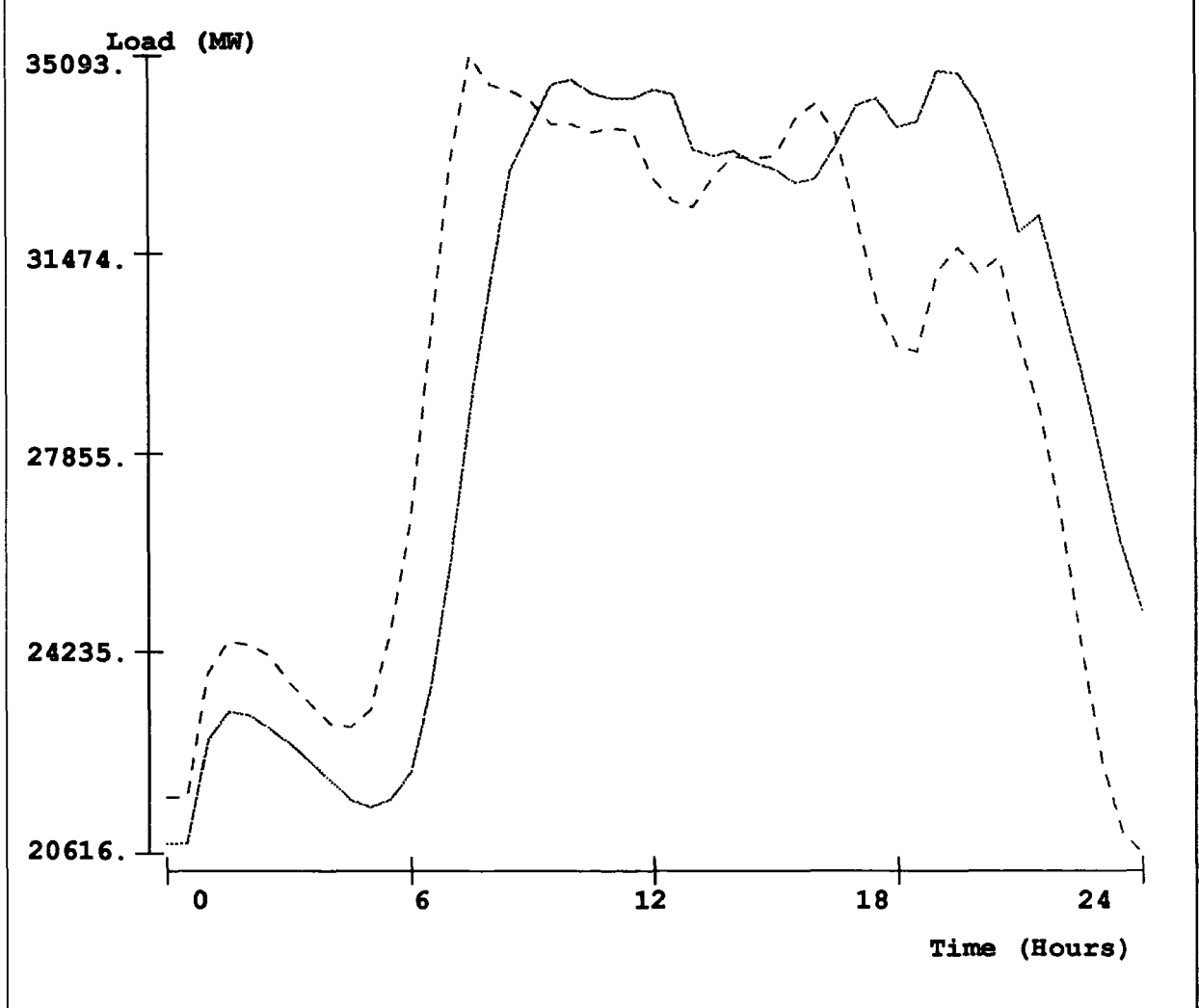


Figure 5.4 Prediction of GMT/BST Effects for Tuesday by ARIMA

TITLE: Prediction Around Time Change-overs (GMT -- BST)

FIGURE: For Wednesday by ARIMA

— Prediction
- - - Act

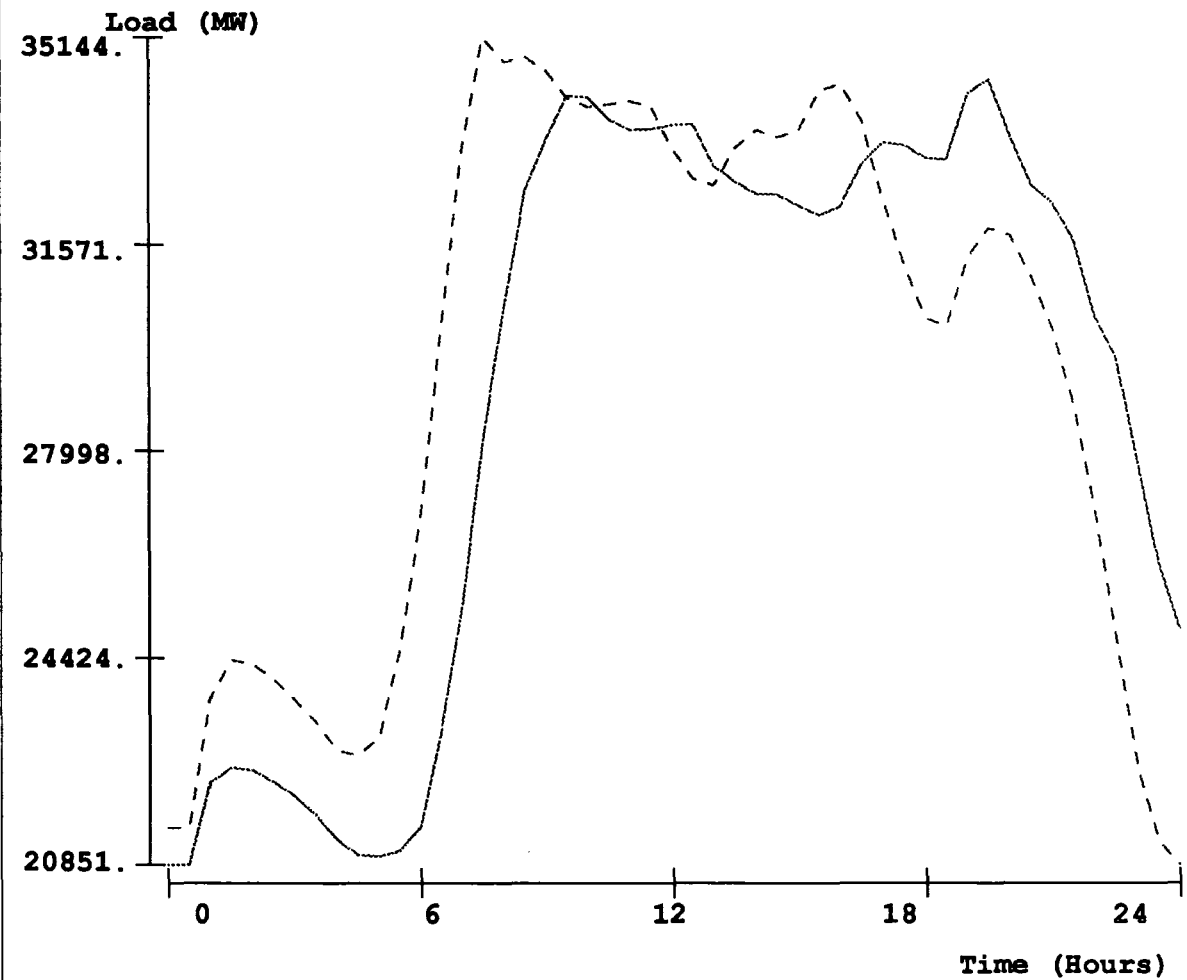


Figure 5.5 Prediction of GMT/BST Effects for Wednesday by ARIMA

TITLE: Prediction Around Time Change-overs (GMT -- BST)

FIGURE: For Thursday by ARIMA

— Prediction
- - - Act

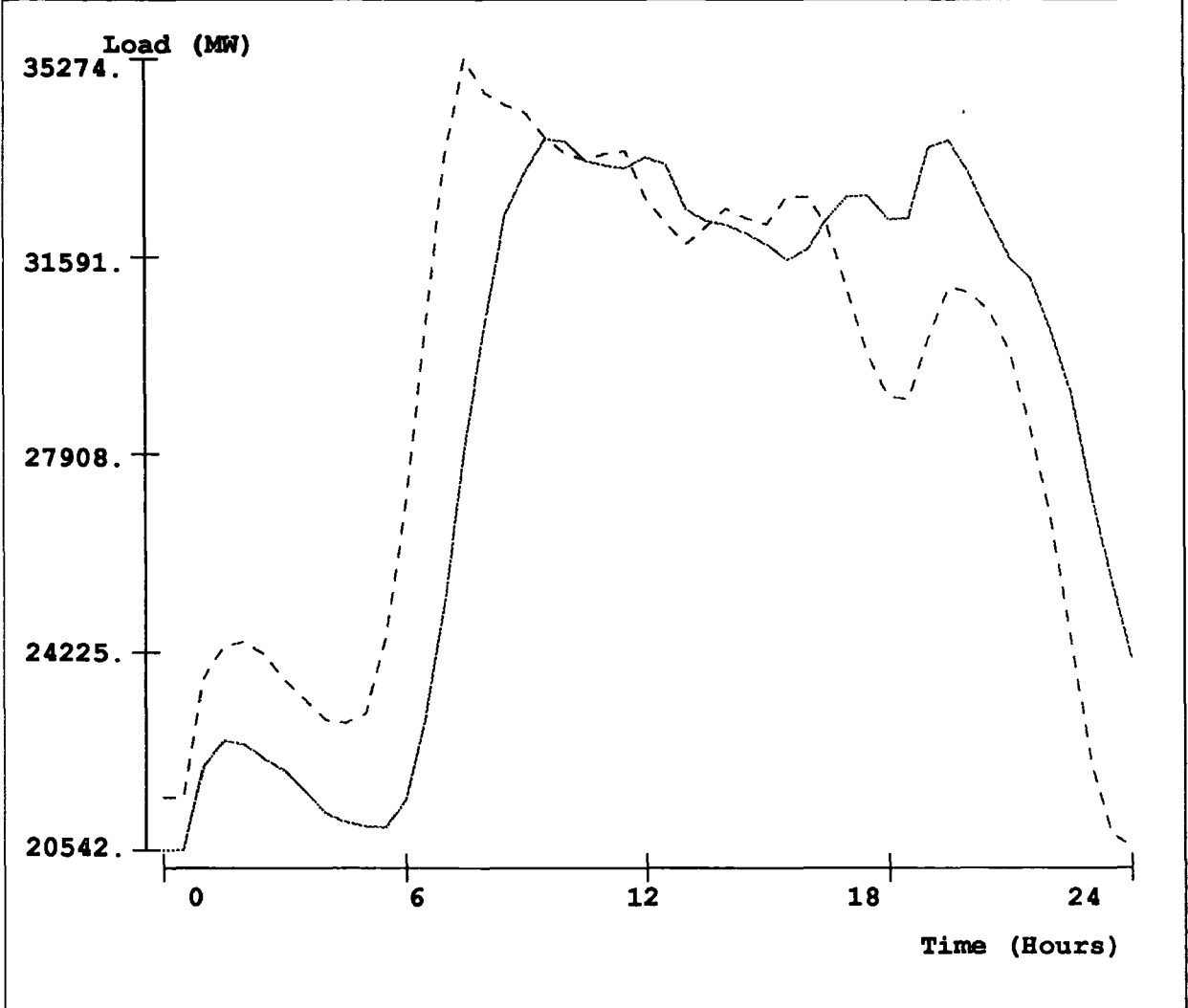


Figure 5.6 Prediction of GMT/BST Effects for Thursday by ARIMA

TITLE: Prediction Around Time Change-overs (GMT -- BST)

FIGURE: For Friday by ARIMA

— Prediction

--- Act

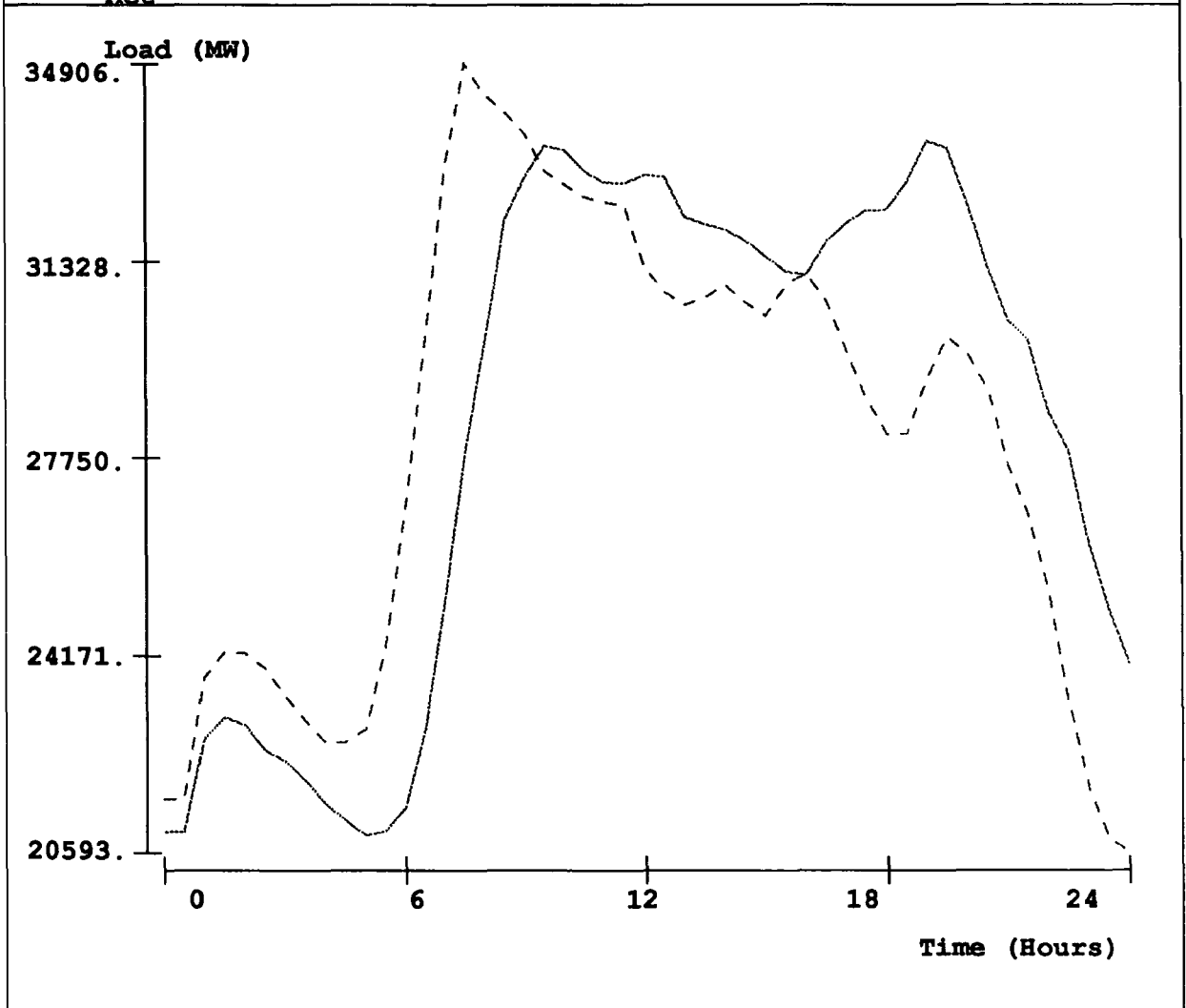


Figure 5.7 Prediction of GMT/BST Effects for Friday by ARIMA

TITLE: Prediction Around Time Change-overs (BST -- GMT)

FIGURE: For Monday by ARIMA

— Prediction

- - - Act

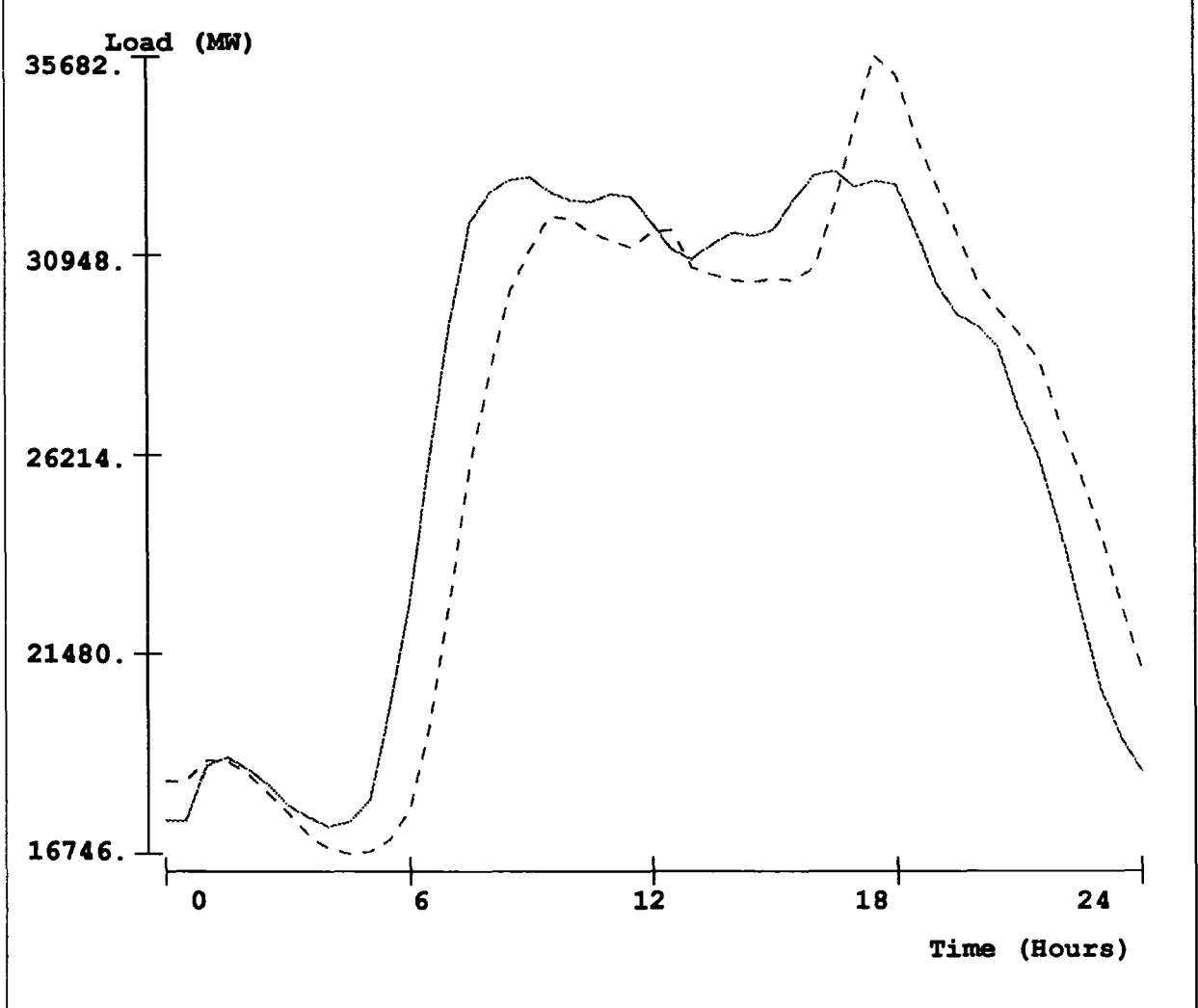


Figure 5.8 Prediction of BST/GMT Effects for Monday by ARIMA

TITLE: Prediction Around Time Change-overs (BST -- GMT)

FIGURE: For Tuesday by ARIMA

— Prediction

- - - Act

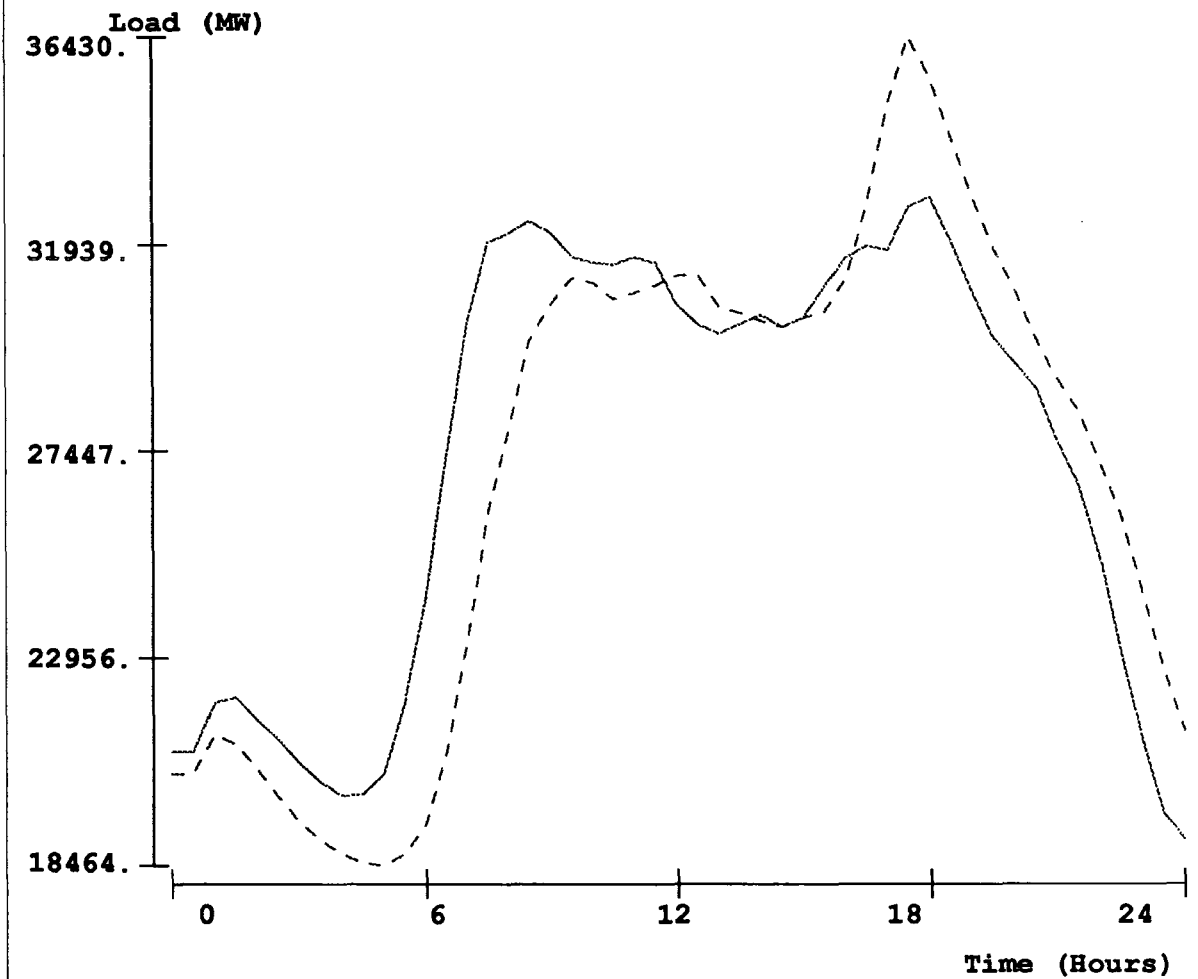


Figure 5.9 Prediction of BST/GMT Effects for Tuesday by ARIMA

TITLE: Prediction Around Time Change-overs (BST -- GMT)

FIGURE: For Wednesday by ARIMA

— Prediction

- - - Act

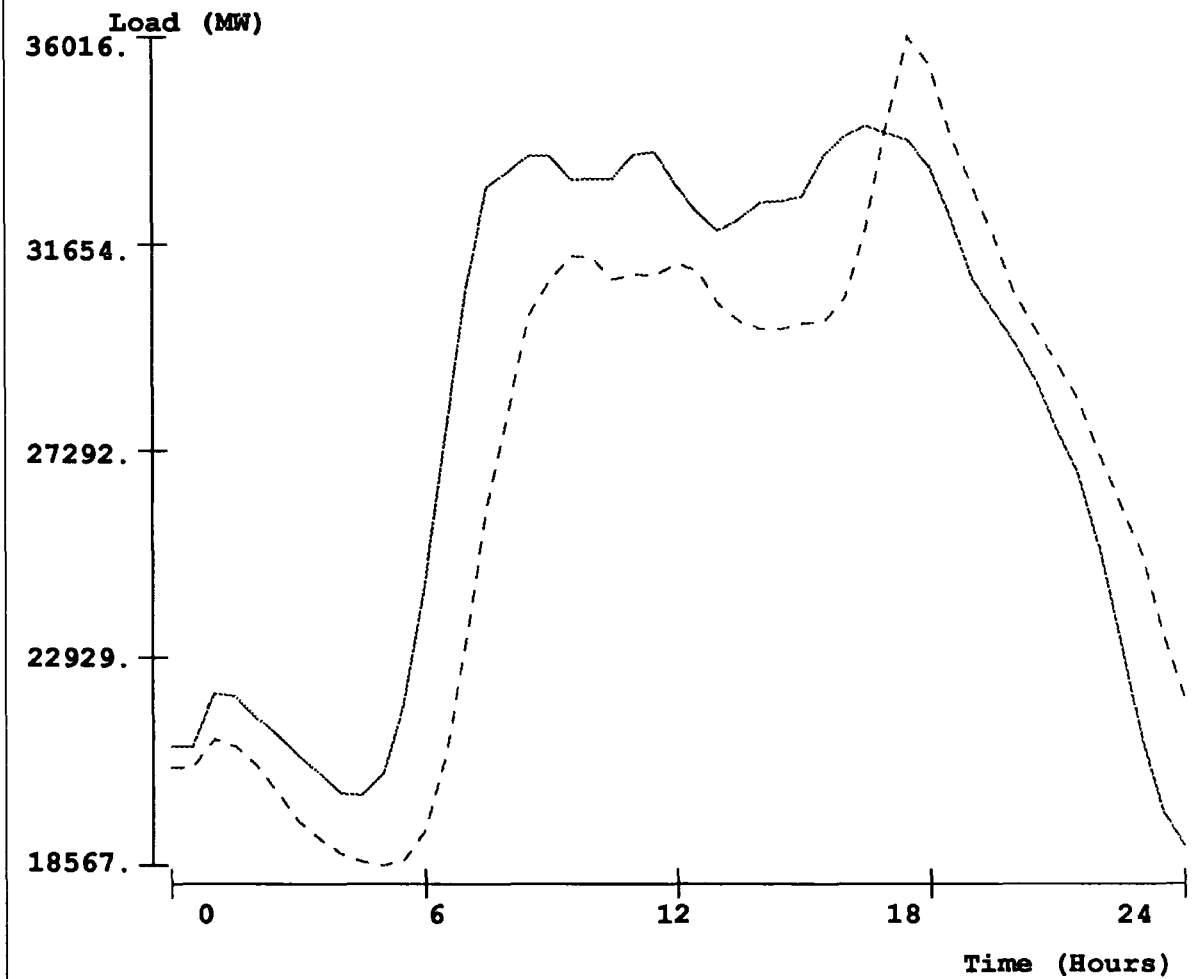


Figure 5.10 Prediction of BST/GMT Effects for Wednesday by ARIMA

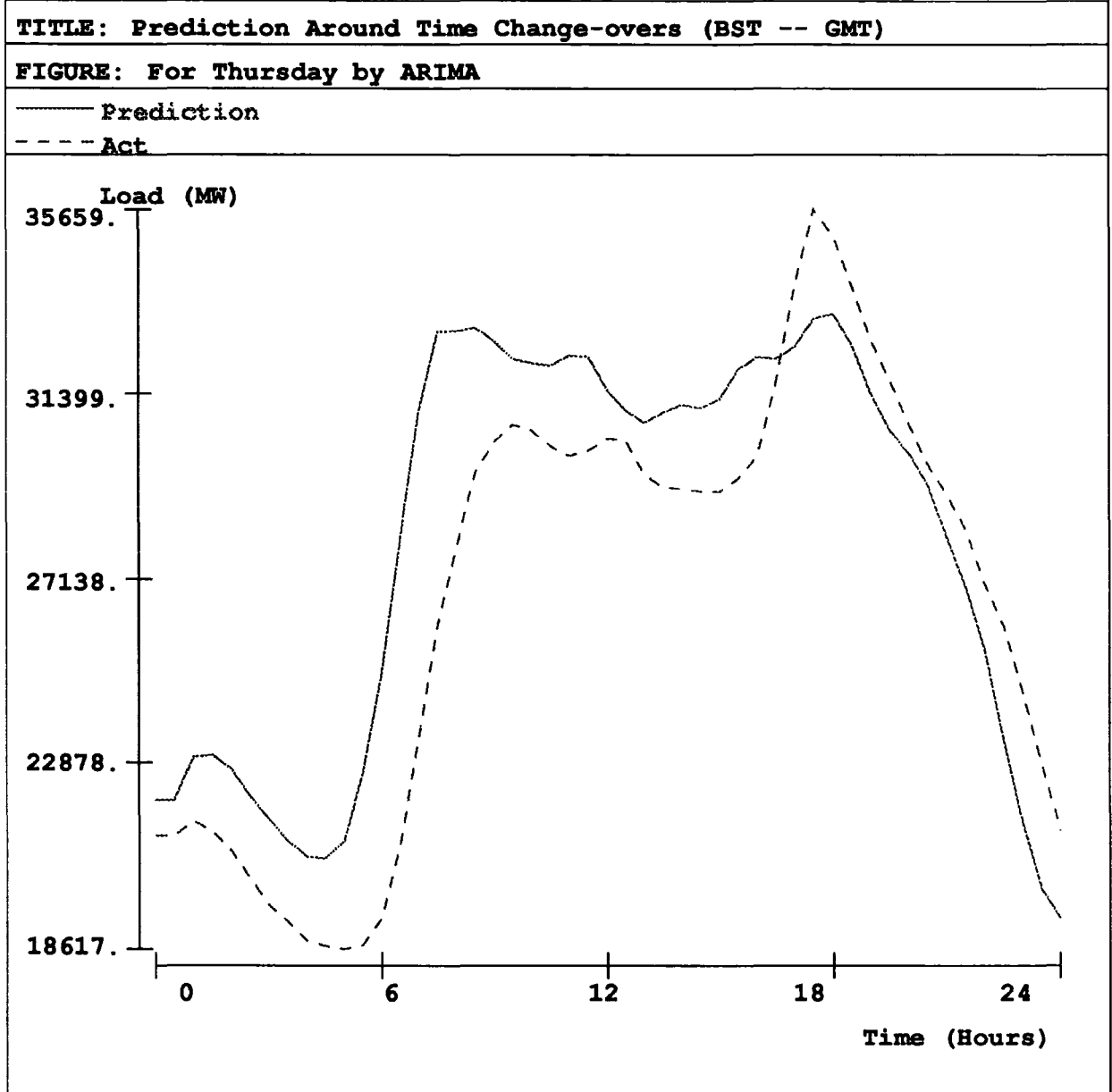


Figure 5.11 Prediction of BST/GMT Effects for Thursday by ARIMA

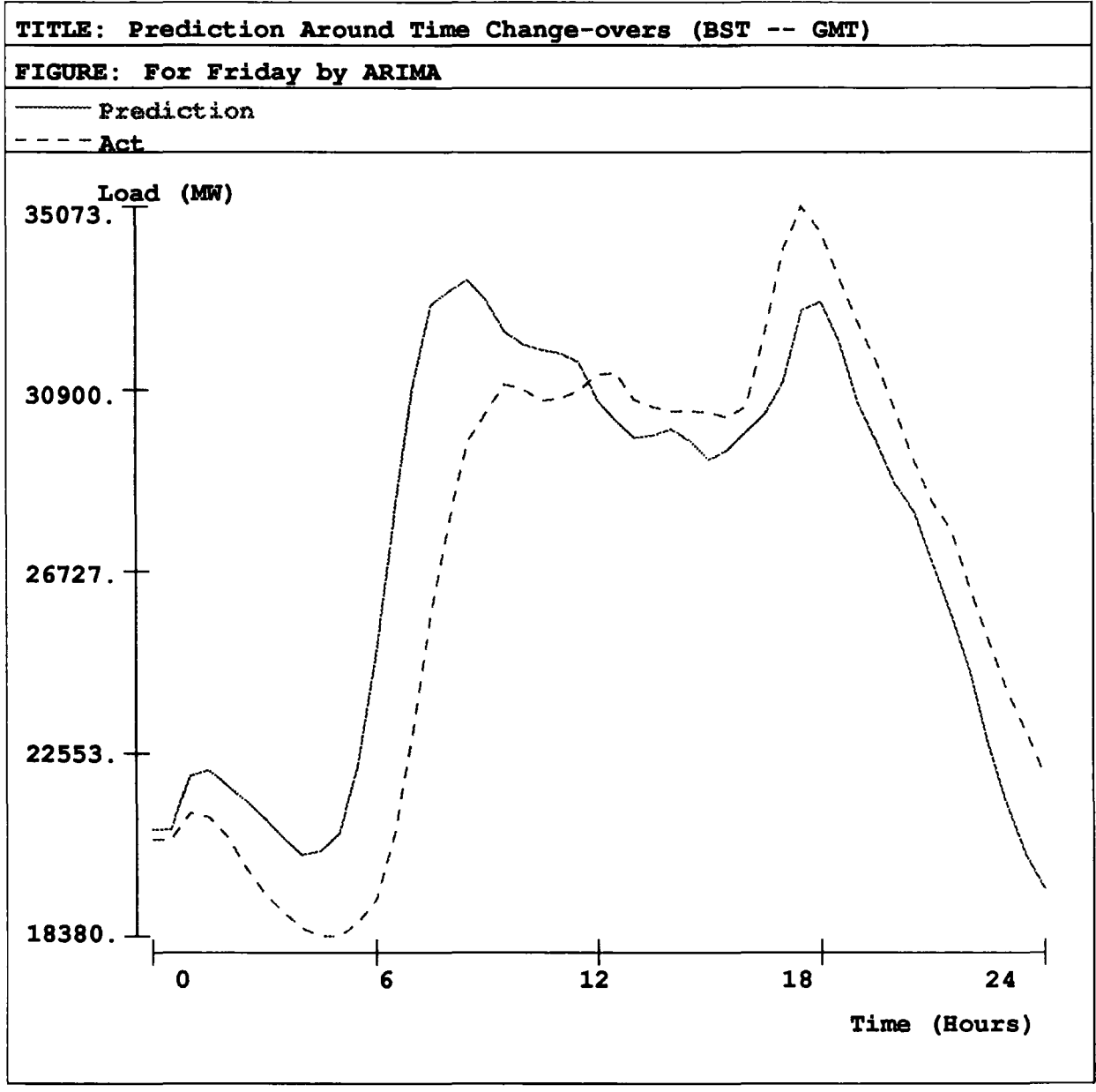


Figure 5.12 Prediction of BST/GMT Effects for Friday by ARIMA

5.4 Prediction by adoption of relative gaps

Since time change-overs influence load behaviours in a similar way each year, load prediction of this period may be easier if the load data of the same period in the past years are available.

The concept of relative gap can be used here, which indicates the difference between the loads before and after the time change-overs.

The first kind of Relative Gap (R. G. 1) is defined [160] as the load difference in megawatts [160]:

$$R.G.1(D, t) = Load_a(D, t) - Load_b(D, t) \quad (5.1)$$

where D is day-of-week, t is GMT time, R. G. 1 is Relative Gap, $Load_b$ is the actual data before time change-over, and $Load_a$ is the actual data after time change-over.

The second kind of Relative Gap (indicated as R. G. 2) is defined in (5.2) [160] as the load difference in percentage between the actual loads before and after the time change-over:

$$R.G.2(D, t) = \frac{Load_a(D, t) - Load_b(D, t)}{Load_b(D, t)} \quad (5.2)$$

So, the current R. G. 1 and R. G. 2 should be obtained in the first instance, if it is assumed that the current year's R. G. 1 and R. G. 2 keep the same as that of the previous years. They can be calculated by applying the above equations with the data of the previous years.

Load prediction by the two relative gaps has been tested against the same loads of the CEGB system around the periods of time change-overs in

1984. Results are listed in Tables 5.3 and 5.4. Figures 5.13 and 5.14 illustrate two examples of the predictions by relative gaps.

**Table 5.3: Results of Prediction by Relative Gaps
(GMT → BST)**

Date	Day-of-week	R. G. 1 (%)		R. G. 2 (%)	
		R.M.S.	Max.	R.M.S.	Max.
26/3/1984	Monday	5.56	10.81	6.29	13.17
27/3/1984	Tuesday	2.66	7.51	2.52	6.71
28/3/1984	Wednesday	4.39	-9.72	4.25	-9.44
29/3/1984	Thursday	5.67	-10.53	5.54	-10.34
30/3/1984	Friday	18.36	-28.61	17.95	-28.73

**Table 5.4: Results of Prediction by Relative Gaps
(BST → GMT)**

Date	Day-of-week	R. G. 1 (%)		R. G. 2 (%)	
		R.M.S.	Max.	R.M.S.	Max.
29/10/1984	Monday	2.48	-5.17	2.48	5.15
30/10/1984	Tuesday	3.77	6.56	3.86	6.61
31/10/1984	Wednesday	6.48	9.35	6.67	9.99
1/11/1984	Thursday	3.59	6.20	3.64	6.50
2/11/1984	Friday	4.04	7.82	4.18	7.89

Both Figures 5.13, 5.14 and Tables 5.3 and 5.4 show that adoption of relative gaps can improve load prediction over time change-overs compared with the ARIMA model (in Tables 5.1 and 5.2). However, it is noticed that the prediction is not so good for Friday in Table 5.3 as for others. The reason is that the Friday in 1983 was a bank holiday: a Good Friday which altered the

TITLE: Prediction Around Time Change-overs (GMT -- BST)

FIGURE: For Wednesday by R.G.1 & R.G.2

—— R.G.1 ····· ACT
----- R.G.2

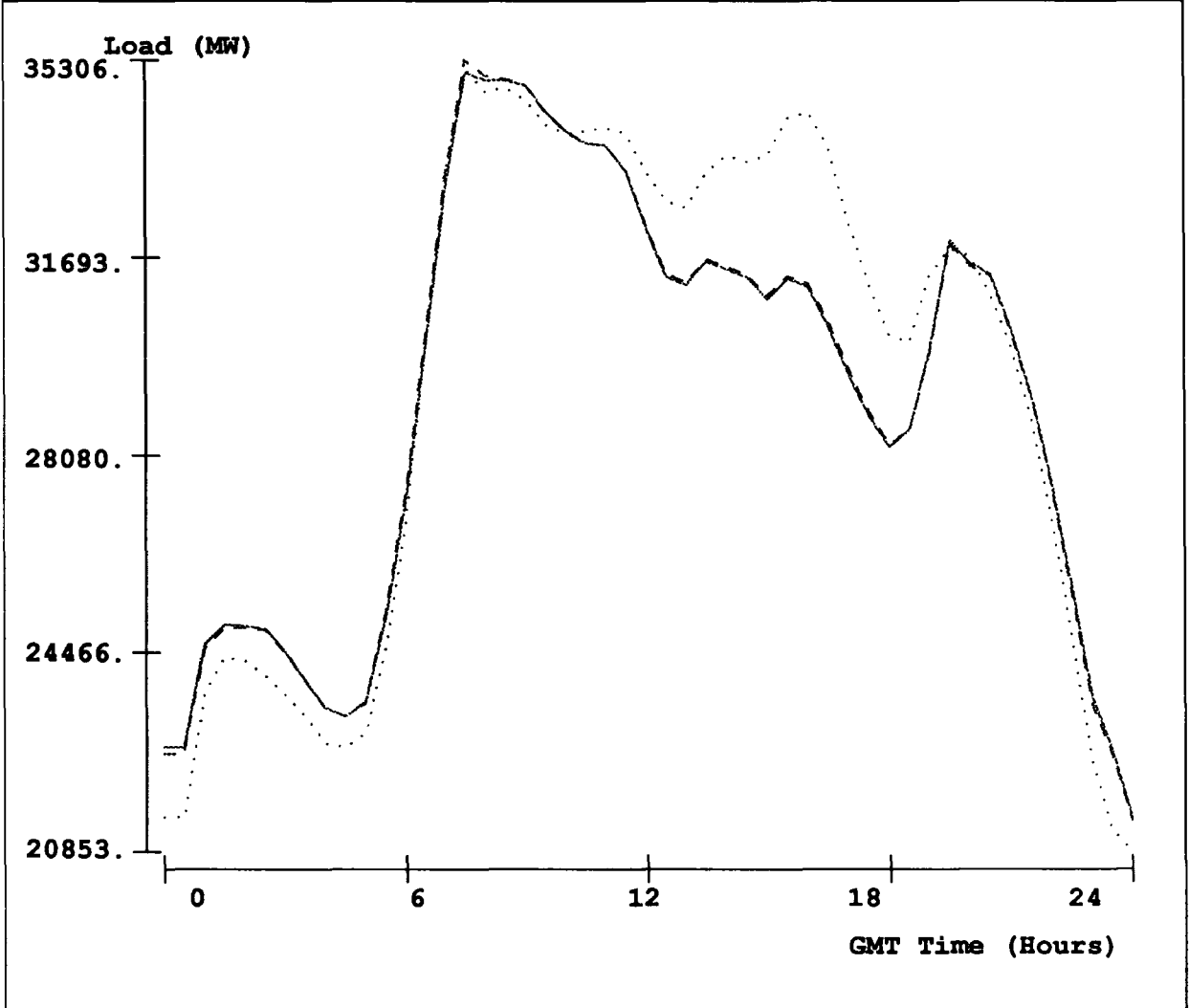


Figure 5.13 Prediction of GMT/BST Effects by R.G.1 and R.G.2

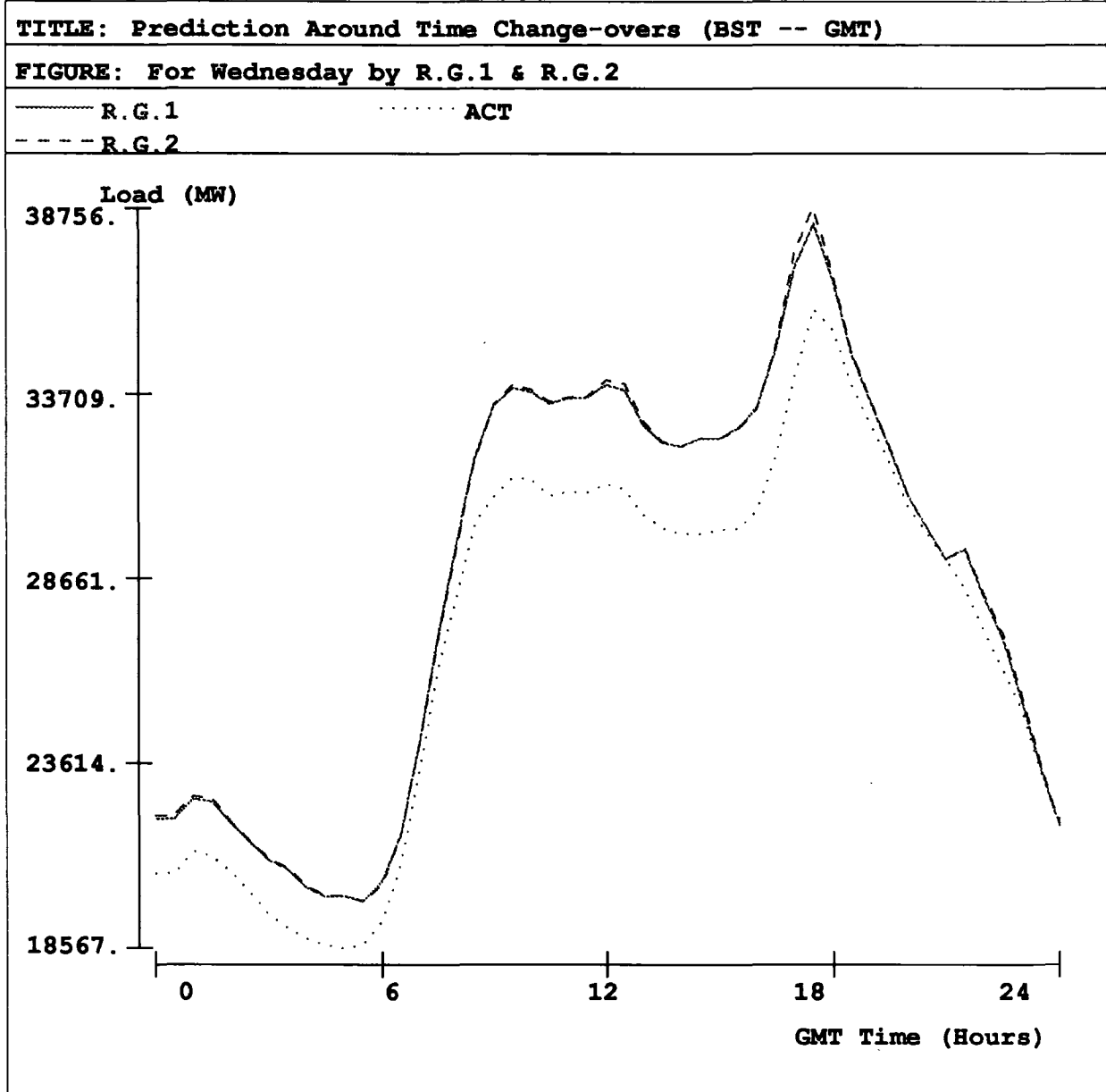


Figure 5.14 Prediction of BST/GMT Effects by R.G.1 and R.G.2

load from the normal Friday load. Also, both tables and figures show little difference between the use of relative gaps in megawatts and in percentage.

It is known that executing the change of time system is mainly to make use of natural sunlight and save energy. Therefore, all the components (except the lighting load which is influenced by the alteration in time of sunrise and sunset) should be adjusted by one hour, if the difference of the actual time of sunrise and sunset from one week to another is neglected. In other words, only the lighting load should be separated from the whole load. This can avoid such cases as that for the Good Friday.

5.5 Expert system approach

The lighting load is assumed to be on 40 minutes after sunset, since the street lights are scheduled on about 40 minutes after sunset. In our case of CEGB system, the average lighting-up time (in the Midlands) are used.

The lighting load in the evening is of the following form:

$$[[posnorm \ 1.0 \ t1 \ 6][const \ 1.0 \ t1 \ t2][negnorm \ 1.0 \ t2 \ 6]]$$

where $t1$ is the lighting-up time and $t2$, the finish time.

The lighting load can be estimated by the approach proposed in chapter 4. Figure 5.15 shows the resulted lighting load profile for the day of 24/10/1984 (under BST) when the lighting-up time was 6:49 pm.

When the lighting load is separated from the overall load in a prediction, it is easy to consider the problem due to the time change-over.

The detailed analysis of the difference in load data prior to time changing and after showed that the period of one day may be divided into three parts for further analysis (see Figure 5.1 and Figure 5.2):

TITLE: Load Components

FIGURE: Lighting Load

----- BG_LIGHT.P

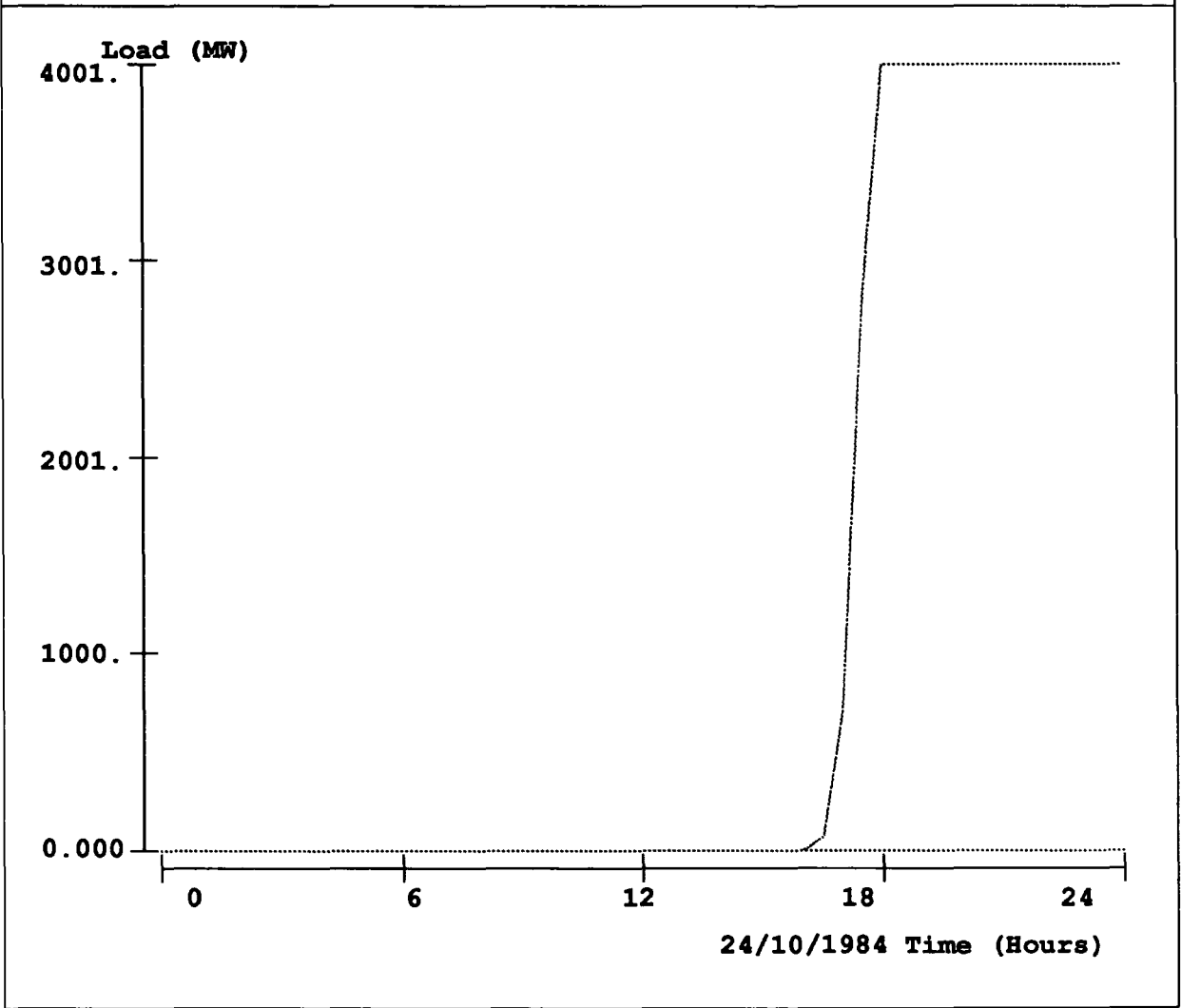


Figure 5.15 The Evening Lighting Load Profile

Part I: from the start of the day (midnight) till the first trough. In this part, the load record after the change showed a similar pattern to that before the change, the trough load seemed to be at the same level.

Part II: from the first trough onwards, till the sunset. During this period, the load seemed to move by one hour.

Part III: from sunset, i.e. the trough occurring when the time system changed from GMT to BST, or the evening peak around dinner time when changing from BST to GMT, till midnight.

According to the different properties among these periods, the prediction can be made for each of the periods separately.

5.5.1 From GMT to BST

In **part I**, it was observed, from the successive years of data, that the loads after time change-over were lower than that before time change-over. So, if it is assumed that the ratio of loads after time change-over to that before time change-over is the same from year to year, then the loads in this part can be estimated.

In **part II**, it seemed that load could be forecast simply by shifting the overall load backward by one hour if the heating factors were excluded.

In **part III**, since the sunset was later than that of one week before, the lighting load was easily calculated based on the time of sunset and the lighting load of last week. Prediction was made by summing the lighting load and the rest of the load which was obtained by shifting by one hour.

Table 5.5 lists the results of predicting the weekday loads following the time change-over in 1984. And Figures 5.16 to 5.20 describe the predicted loads and the actual loads of the week following the GMT/BST change-over in 1984. It can be seen that the expert system approach can predict the time

change-over effects whilst the ARIMA method can not. Although the evening peak load and time of Monday can not be correctly predicted, the expert system approach can give better and better predictions when the affected loads are available.

5.5.2 From BST to GMT

In part I, from the successive years of data, it was observed that the trough load was at the same level as before time change-over, and the peak load was at the same level as the final load on the previous day. The time when the peak and trough loads happen can be drawn from the previous year.

In part II, it seemed that load could be forecast simply by shifting the overall load forward by one hour if the heating factors were not considered.

In part III, since the sunset was earlier than that of one week before, the lighting load was easily estimated based on the time of sunset and the lighting load of last week. Prediction was made by summing the lighting load and the rest of the load which was obtained by shifting by one hour.

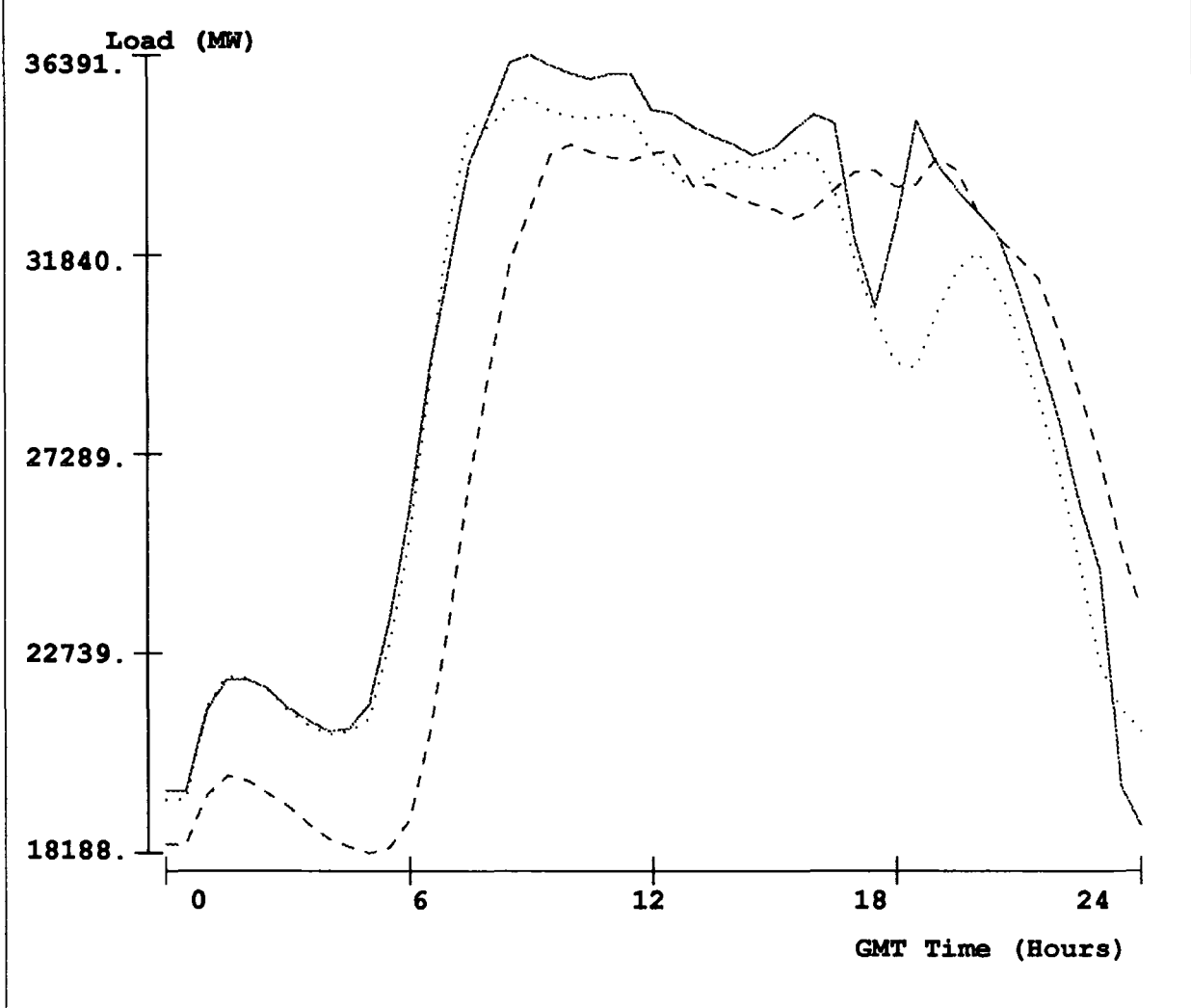
**Table 5.5: Prediction by Expert System
(GMT → BST)**

Date	Day-of-week	Original ARIMA (%)		Expert System (%)	
		R.M.S.	Max.	R.M.S.	Max.
26/3/1984	Monday	10.03	-27.67	4.94	19.21
27/3/1984	Tuesday	10.86	24.95	2.62	12.15
28/3/1984	Wednesday	10.67	-23.67	2.37	-5.84
29/3/1984	Thursday	10.89	-24.55	1.44	4.49
30/3/1984	Friday	11.01	-23.54	2.15	5.10

TITLE: Prediction Around Time Change-overs (GMT -- BST)

FIGURE: For Monday by ARIMA & ES

—— MON_ES.P ····· MON_ACT.P
- - - - MON_AR.P



5.16 Prediction of GMT/BST Effects for Monday by ES

TITLE: Prediction Around Time Change-overs (GMT -- BST)

FIGURE: For Tuesday by ARIMA & ES

—— TUES_ES.P ····· TUES_ACT.P
- - - TUES_AR.P

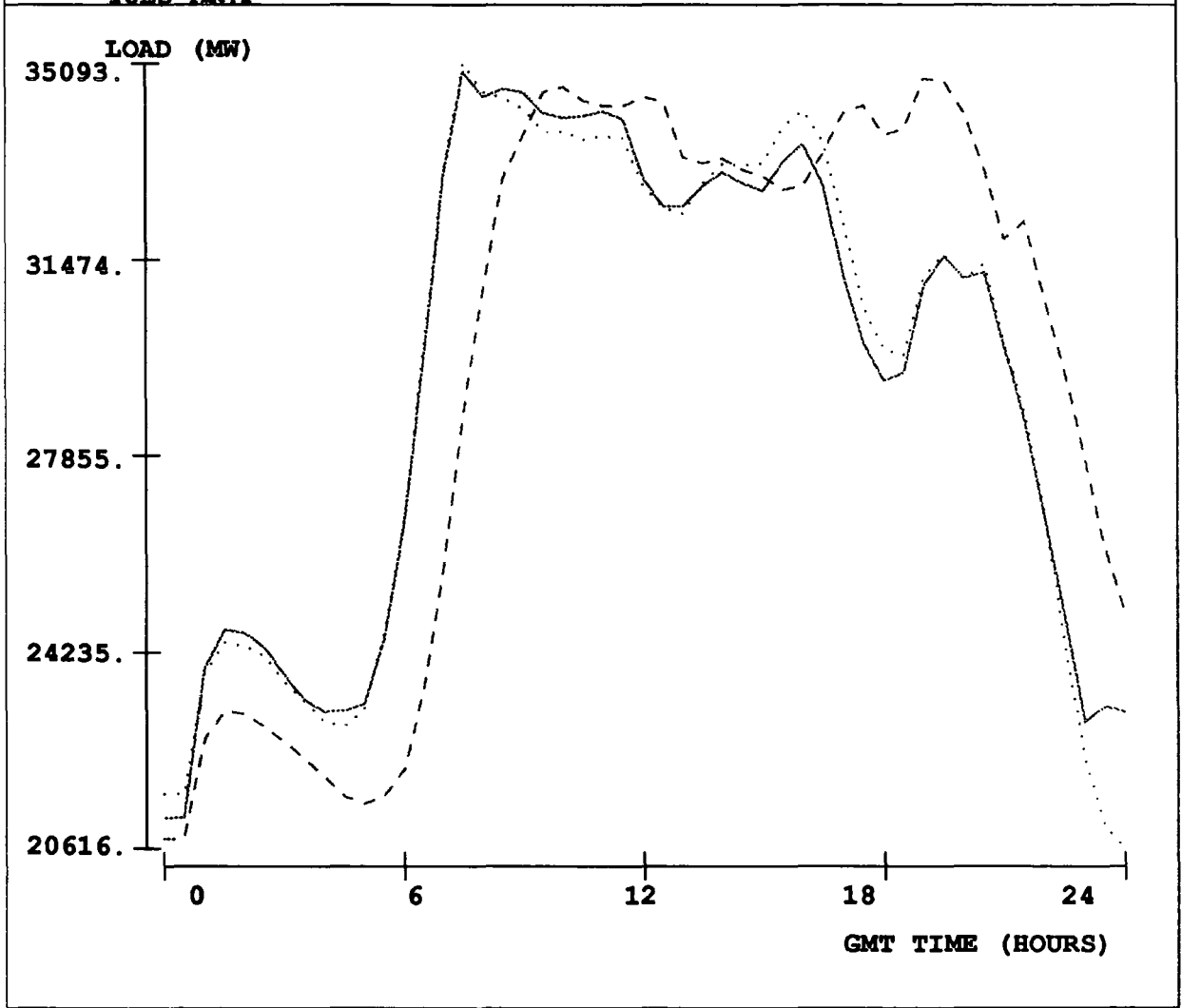


Figure 5.17 Prediction of GMT/BST Effects for Tuesday by ES

TITLE: Prediction Around Time Change-overs (GMT -- BST)

FIGURE: For Wednesday by ARIMA & ES

—— WED_ES.P ····· WED_ACT.P
- - - - WED_AR.P

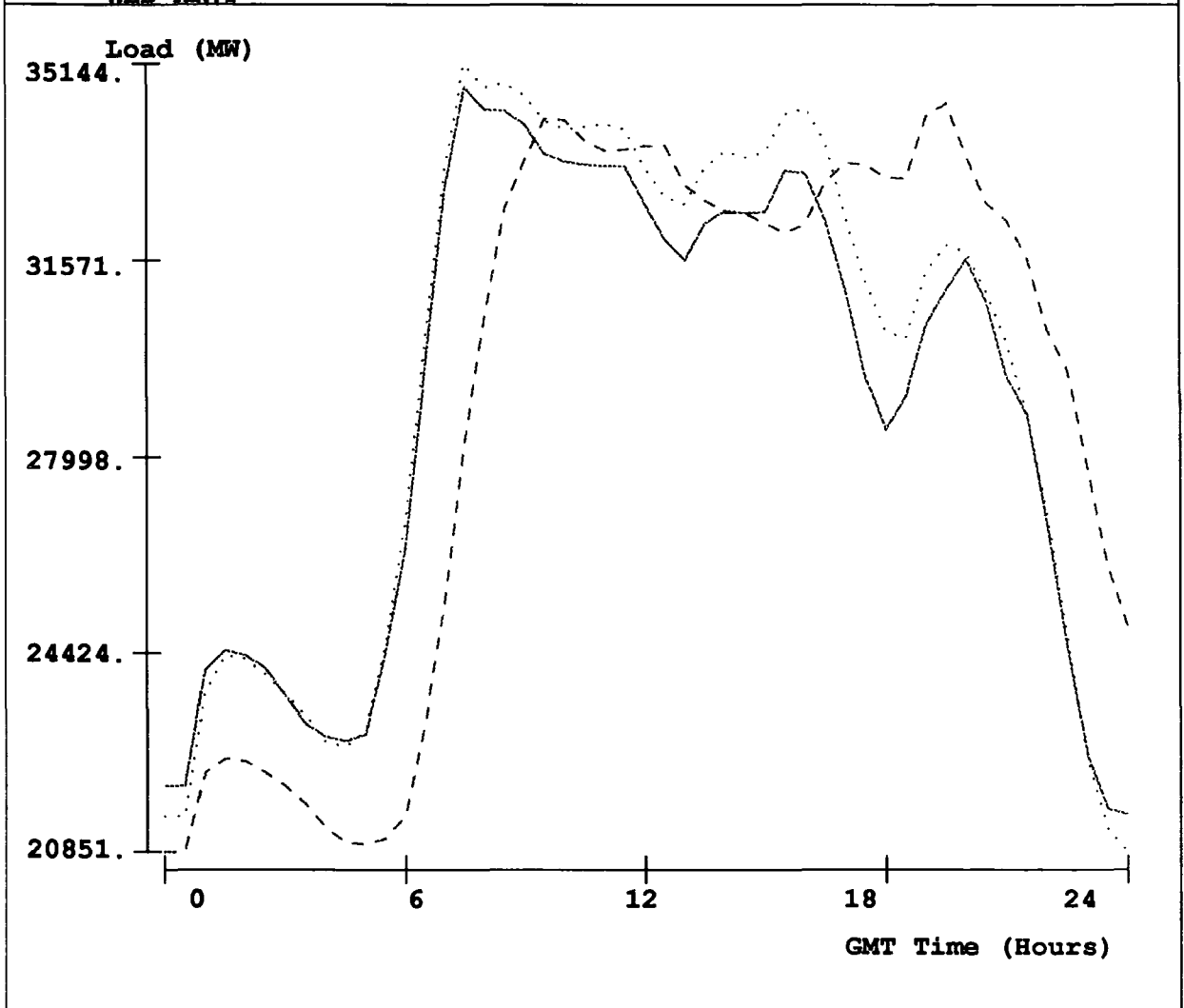


Figure 5.18 Prediction of GMT/BST Effects for Wednesday by ES

TITLE: Prediction Around Time Change-overs (GMT -- BST)

FIGURE: For Thursday by ARIMA & ES

—— THUR_ES.P ····· THUR_ACT.P
- - - - THUR_AR.P

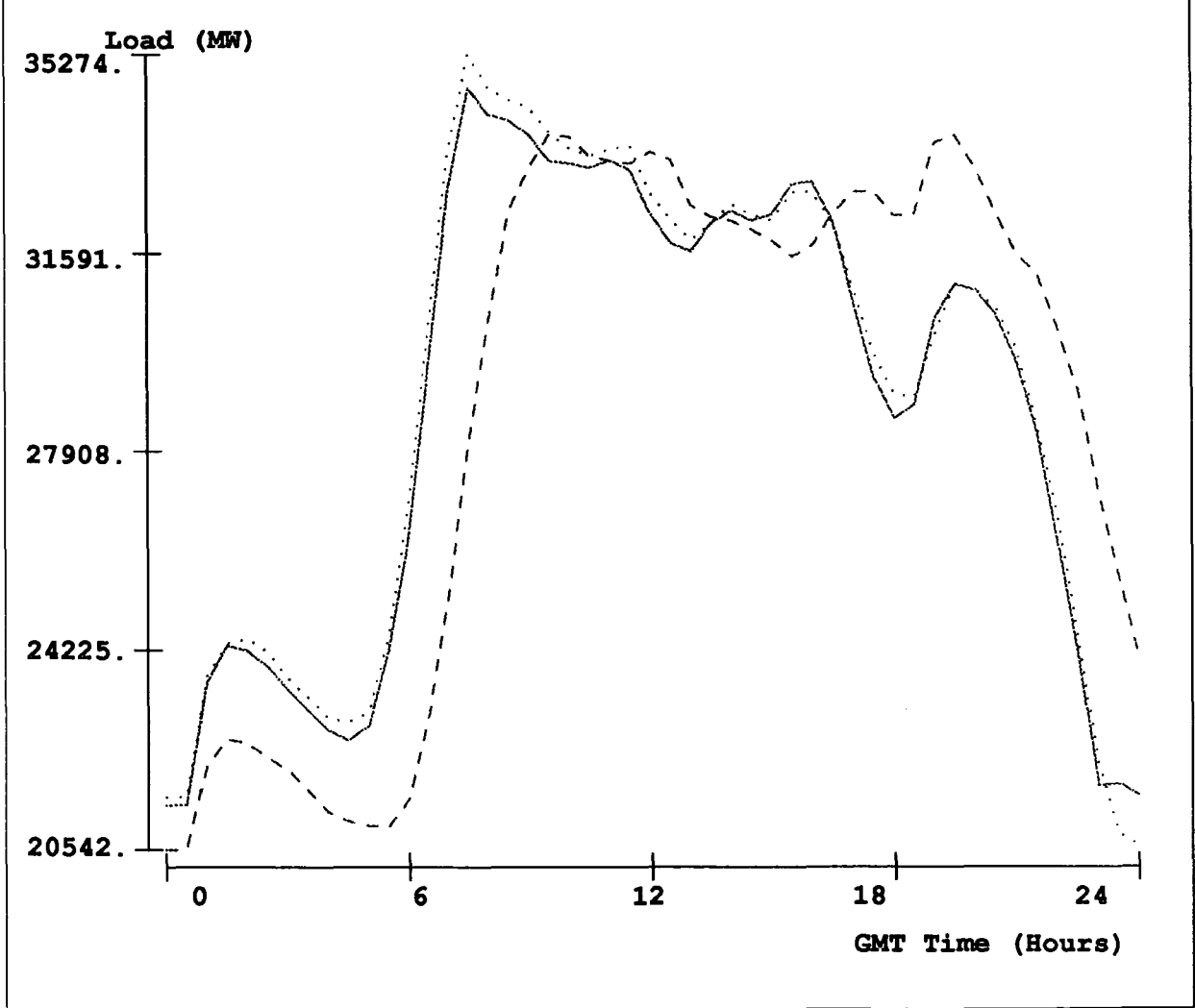


Figure 5.19 Prediction of GMT/BST Effects for Thursday by ES

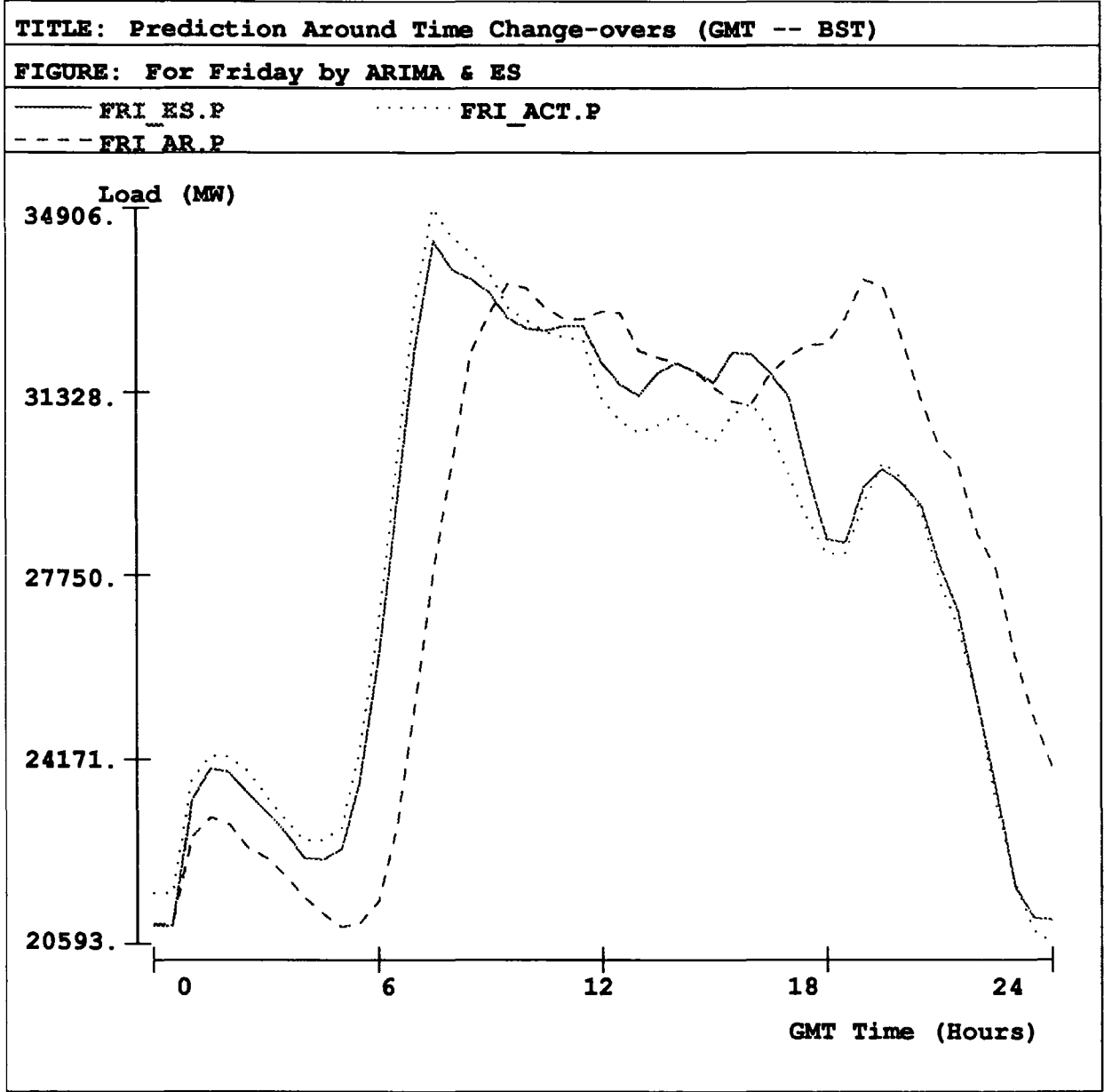


Figure 5.20 Prediction of GMT/BST Effects for Friday by ES

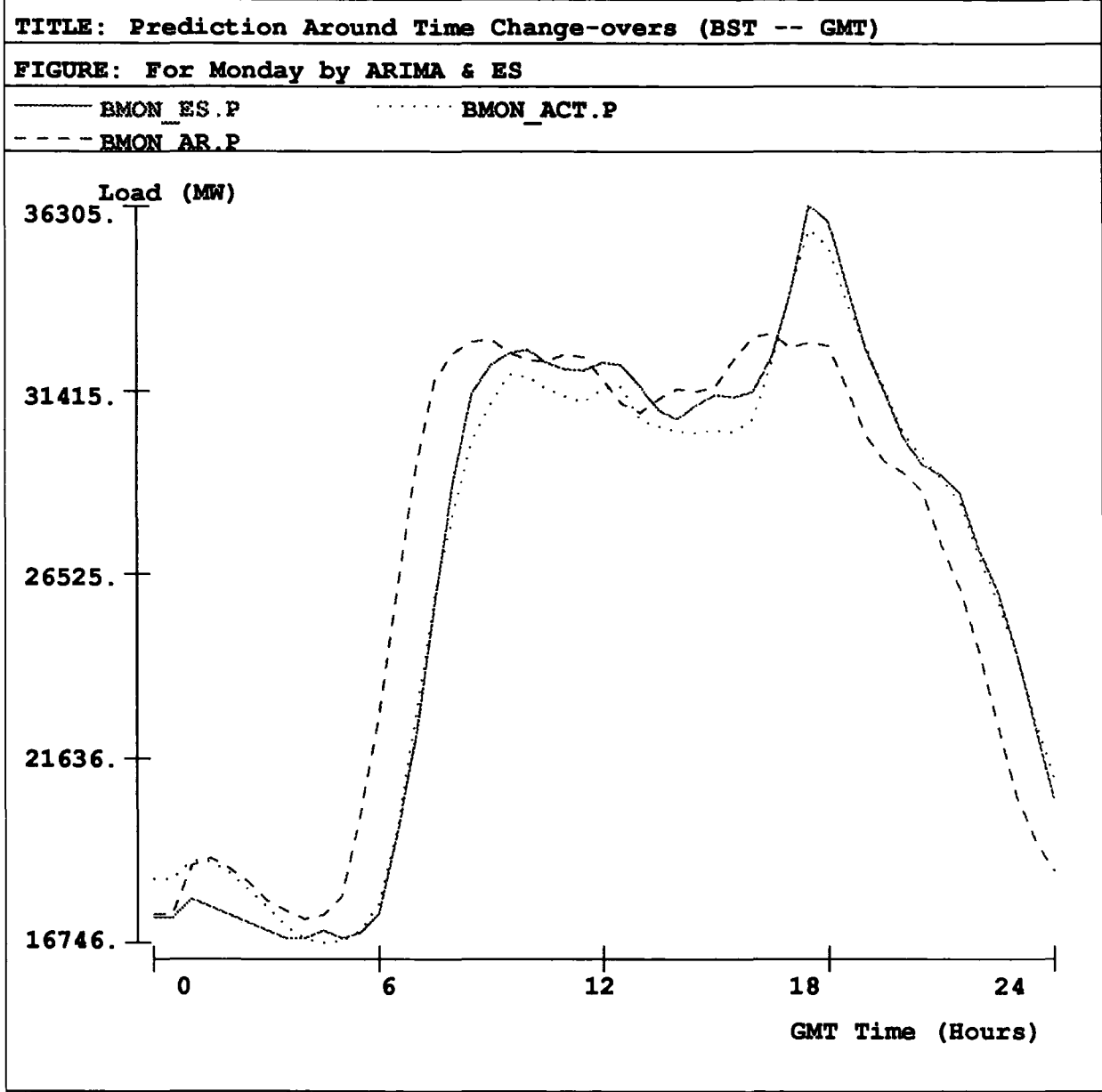


Figure 5.21 Prediction of BST/GMT Effects for Monday by ES

TITLE: Prediction Around Time Change-overs (BST -- GMT)

FIGURE: For Tuesday by ARIMA & ES

----- BTUES_ES.P BTUES_ACT.P
----- BTUES_AR.P

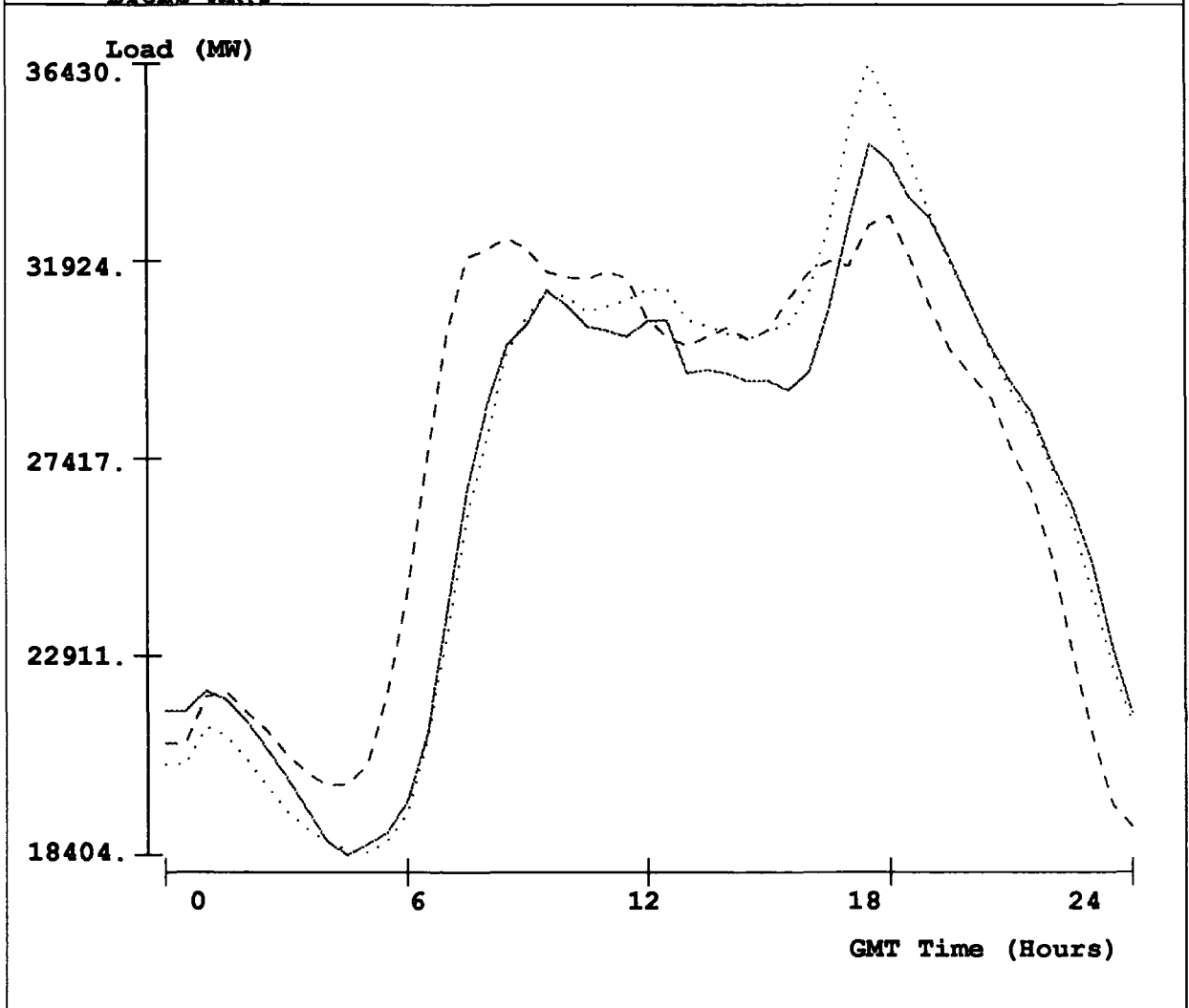


Figure 5.22 Prediction of BST/GMT Effects for Tuesday by ES

TITLE: Prediction Around Time Change-overs (BST -- GMT)

FIGURE: For Wednesday by ARIMA & ES

----- BWED_ES.P ······ BWED_ACT.P
----- BWED_AR.P

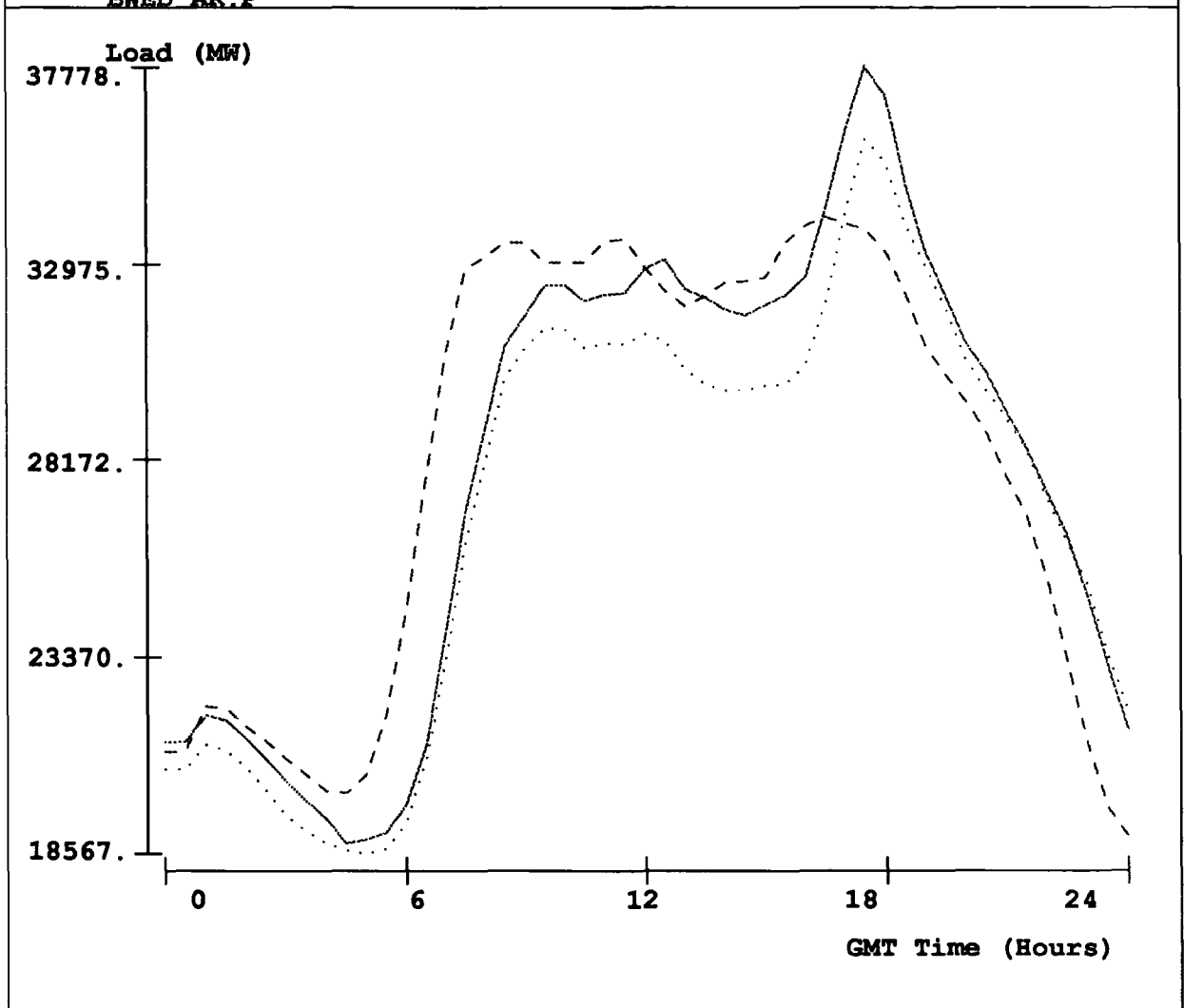


Figure 5.23 Prediction of BST/GMT Effects for Wednesday by ES

TITLE: Prediction Around Time Change-overs (BST -- GMT)

FIGURE: For Thursday by ARIMA & ES

—— BTHUR_ES.P ······ BTHUR_ACT.P
- - - - BTHUR_AR.P

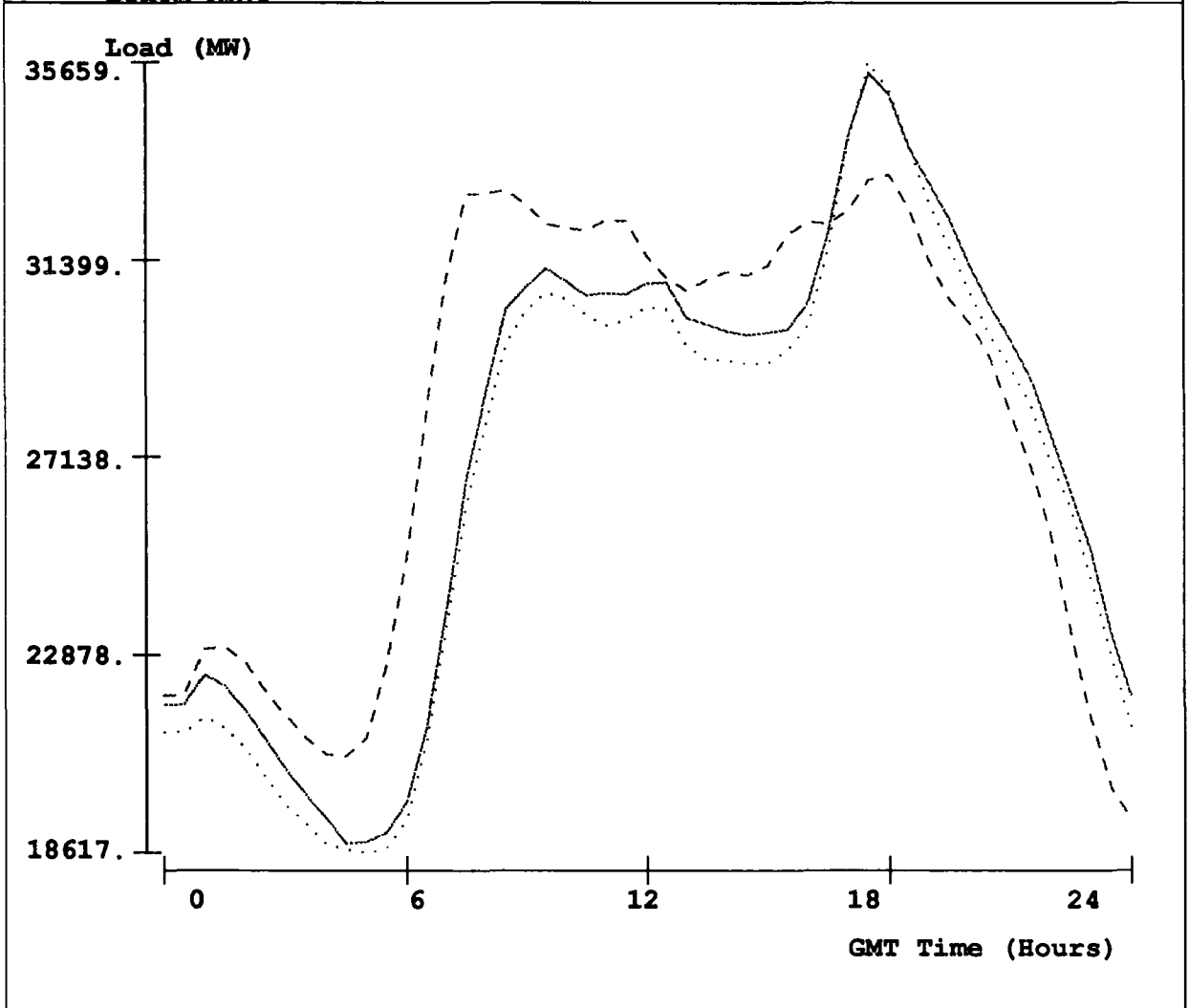


Figure 5.24 Prediction of BST/GMT Effects for Thursday by ES

TITLE: Prediction Around Time Change-overs (BST -- GMT)

FIGURE: For Friday by ARIMA & ES

—— BFRI_ES.P ····· BFRI_ACT.P
- - - - BFRI_AR.P

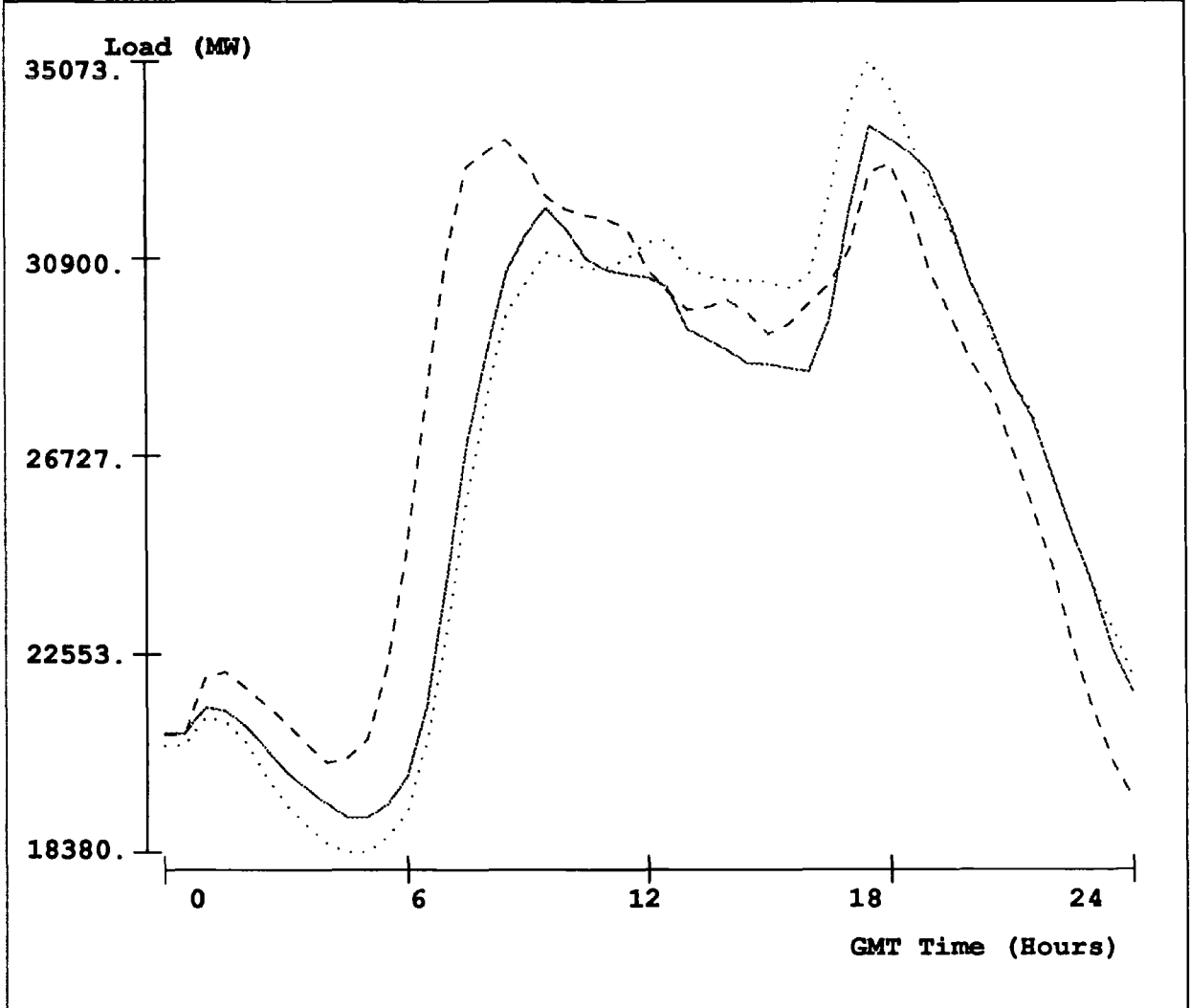


Figure 5.25 Prediction of BST/GMT Effects for Friday by ES

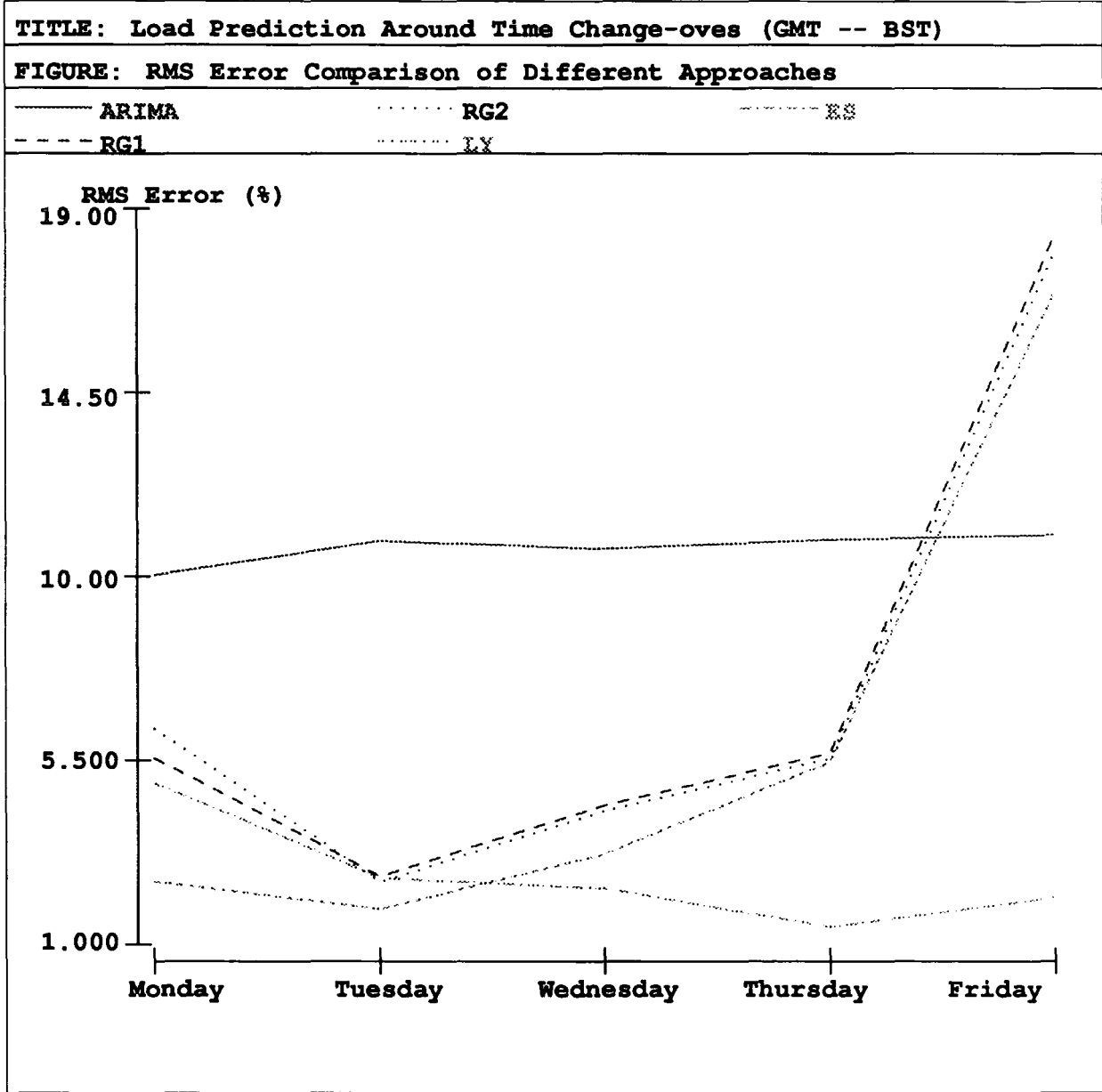


Figure 5.26 RMS Errors of Different Approaches (GMT/BST)

TITLE: Load Prediction Around Time Change-overs (GMT -- BST)

FIGURE: Max. Error Comparison of Different Approaches

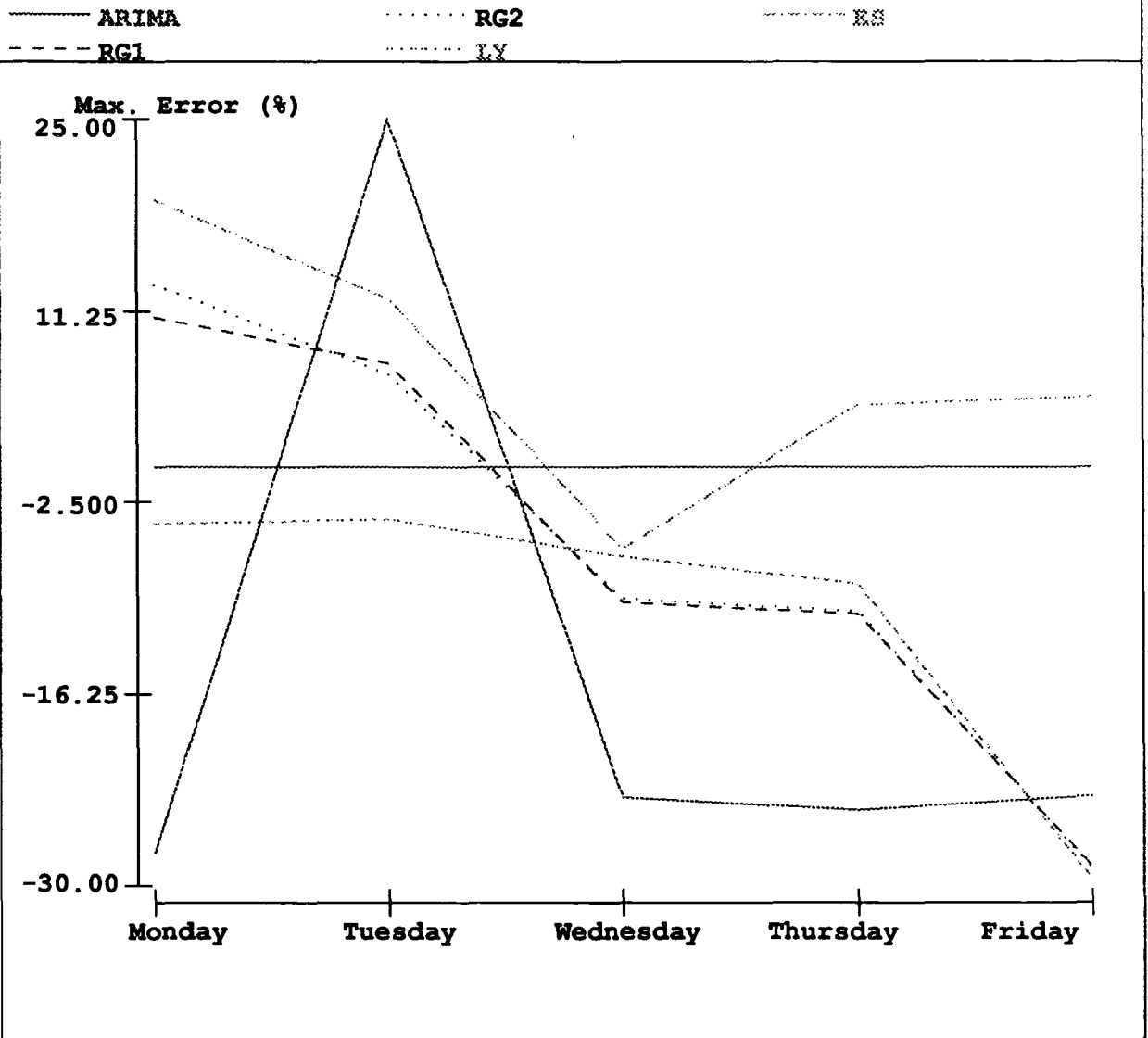


Figure 5.27 Max. Errors of Different Approaches (GMT/BST)

TITLE: Load Prediction Around Time Change-overs (BST -- GMT)

FIGURE: RMS Error Comparison of Different Approaches

— ARIMA ····· RG2 - - - - X X
- - - - RG1 ····· LY

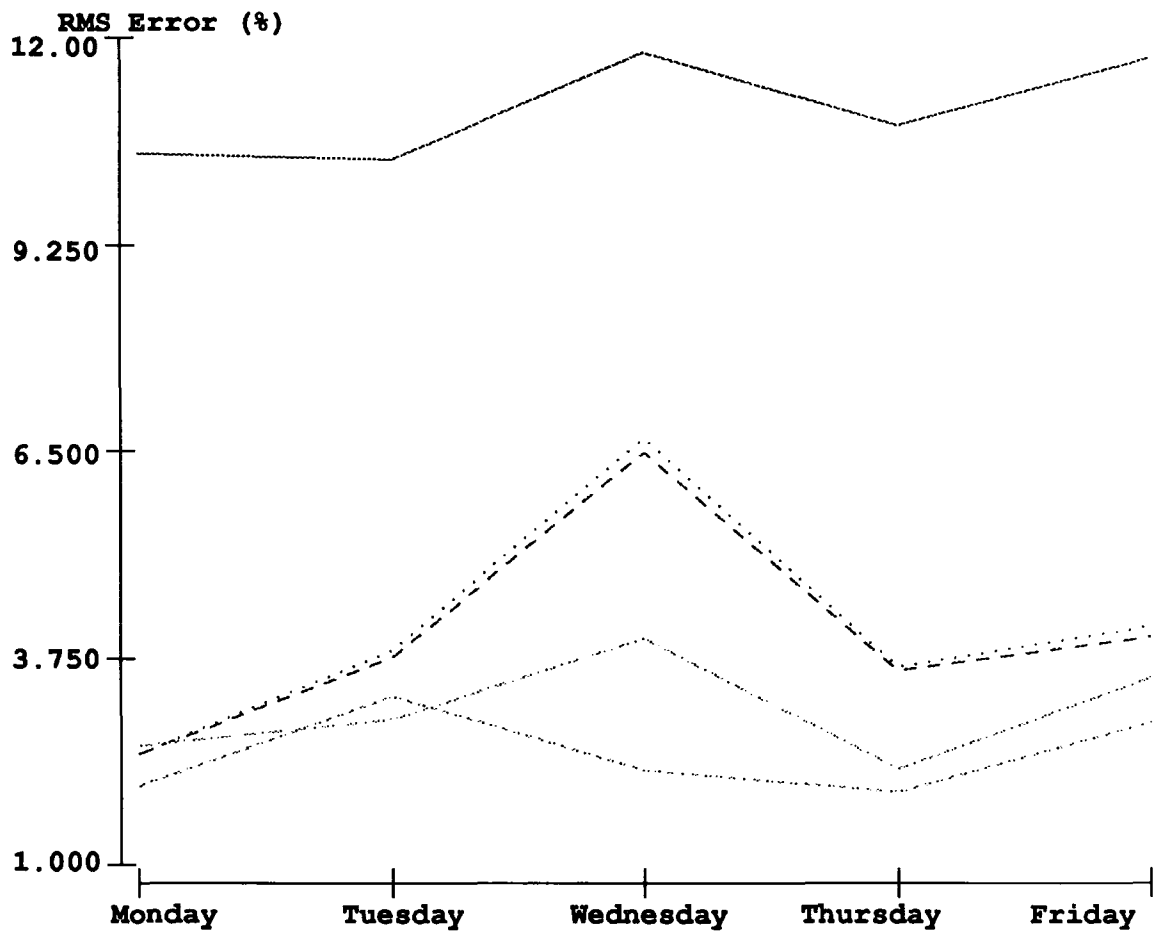


Figure 5.28 RMS Errors of Different Approaches (BST/GMT)

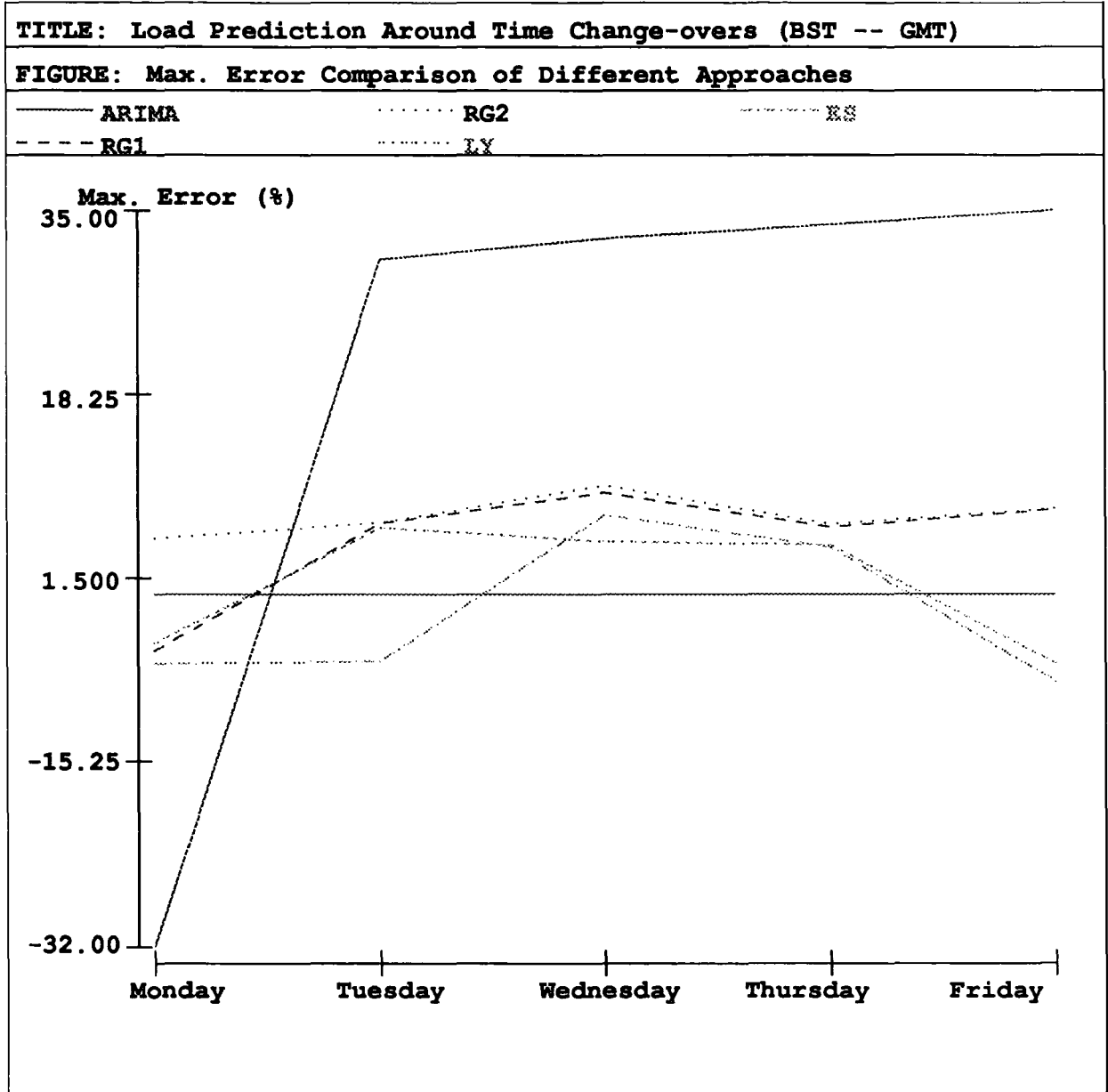


Figure 5.29 Max. Errors of Different Approaches (BST/GMT)

**Table 5.6: Prediction by Expert System
(BST → GMT)**

Date	Day-of-week	Original ARIMA (%)		Expert System(%)	
		R.M.S.	Max.	R.M.S.	Max.
29/10/1984	Monday	10.46	-31.95	2.59	-6.35
30/10/1984	Tuesday	10.39	30.48	2.94	-6.12
31/10/1984	Wednesday	11.80	32.42	4.02	7.31
1/11/1984	Thursday	11.84	33.67	2.28	4.35
2/11/1984	Friday	11.73	34.99	3.49	-8.04

By this process, one week of loads around the time change-over from BST to GMT in 1984 were predicted. The results are shown in Table 5.6 and Figures 5.21 to 5.25.

We can see from Figures 5.16 to 5.25 that by this method, the predicted loads have similar shapes to the actual ones which are quite different from those before the time change-overs.

The procedures in POP-11 to predict loads around the time change-overs are demonstrated in appendix 3.

5.6 Knowledge about lighting-up loads

The following weather information, as an example, is stored in the knowledge base which is used to estimate the lighting load. The last element in the list following the date is the lighting-up time (in slots in GMT time) for that day.

```
[26 3 1984 13 monday]
[10.4 5.6 5.7 234]
[27 3 1984 13 tuesday]
```

[10.2 3.5 5.8 234]
 [28 3 1984 13 wednesday]
 [7.7 0.5 3.6 235]
 [29 3 1984 13 thursday]
 [11.0 2.6 3.6 235]
 [30 3 1984 13 friday]
 [11.8 -0.3 3.3 235]
 [29 10 1984 44 monday]
 [0 0 0 201]
 [30 10 1984 44 tuesday]
 [0 0 0 201]
 [31 10 1984 44 wednesday]
 [0 0 0 201]
 [1 11 1984 44 thursday]
 [0 0 0 200]
 [2 11 1984 44 friday]
 [0 0 0 200]

The detailed procedures of load prediction around time change-overs are listed in appendix 3.

5.7 Assessment of different approaches

There is another commonly used method to estimate the load around the time change-overs, i.e., directly using the load data of the same period in previous years as the prediction loads. Generally speaking, it is reasonably correct, since the utilisation of electricity is more or less the same from the viewpoint of end-use and the similar weather conditions.

Tables 5.7 and 5.8 and Figures 5.26 to 5.29 compare the approach with the other four approaches introduced in previous sections in predicting the weekday loads of the week following the time change-overs.

Table 5.7: Prediction by Different Approaches *
(GMT → BST)

Approach	Error (%)	Monday 26/3/1984	Tuesday 27/3/1984	Wednesday 28/3/1984	Thursday 29/3/1984	Friday 30/3/1984
1	R.M.S.	10.03	10.86	10.67	10.89	11.01
	Max.	-27.67	24.95	-23.67	-24.55	-23.54
2	R.M.S.	5.56	2.66	4.39	5.67	18.36
	Max.	10.81	7.51	-9.72	-10.53	-28.61
3	R.M.S.	6.29	2.52	4.25	5.54	17.95
	Max.	13.17	6.71	-9.44	-10.34	-28.73
4	R.M.S.	2.53	1.87	3.20	5.45	16.97
	Max.	-4.08	-3.72	-6.40	-8.37	-29.55
5	R.M.S.	4.94	2.62	2.37	1.44	2.15
	Max.	19.21	12.15	-5.84	4.49	5.10

It can be seen from Table 5.7 that the expert system method is not so good at predicting the first two days as the load data of last year. The reason is that the proportion of lighting load in the overall load is not very accurate. But for the later three days, it is comparable with the one from last year. A problem may be encountered while using the load data of last year. It is that the time of changing from GMT to BST is usually in the end of March in which Easter weekends may locate. The difficulty is that sometimes both of them occur at the same time, but sometimes not. However, the method of expert systems, can use the pattern matching to find the appropriate reference load. For example, if the time change-over of this year occurs at the Easter weekend, it will first try to find if there is the same case occurring in the past and use the load as the reference. If it fails, it will use the procedure which is

* See notes following Table 5.8.

suitable for holiday prediction, using the corresponding reference to the Easter holiday.

**Table 5.8: Prediction by Different Approaches
(BST → GMT)**

Approach	Error (%)	Monday	Tuesday	Wednesday	Thursday	Friday
		29/10/1984	30/10/1984	31/10/1984	1/11/1984	2/11/1984
1	R.M.S.	10.46	10.39	11.80	10.84	11.73
	Max.	-31.95	30.48	32.427	33.675	34.99
2	R.M.S.	2.48	3.77	6.48	3.59	4.04
	Max.	-5.17	6.56	9.33	6.20	7.82
3	R.M.S.	2.48	3.86	6.67	3.64	4.18
	Max.	5.15	6.61	9.99	6.50	7.89
4	R.M.S.	2.05	3.25	2.26	1.97	2.90
	Max.	-4.48	6.14	4.87	4.54	-6.35
5	R.M.S.	2.59	2.94	4.02	2.28	3.49
	Max.	-6.35	-6.12	7.31	4.35	-8.04

Notes:

R.M.S. Error: root mean squared error;

Max. Error: maximum absolute error;

Approach 1: the original ARIMA;

Approach 2: R. G. 1;

Approach 3: R. G. 2;

Approach 4: estimation based on the last year's data;

Approach 5: the expert system approach.

Although in Table 5.8 the prediction of the expert system approach does not improve on the one from last year's data, the expert system approach can be comparable with the method of relative gaps. Because the relative gaps use the load of the same day-of-week in previous week as a reference, as well as

TITLE: Prediction Around Time Change-overs (GMT -- BST)

FIGURE: Comparison of Three Approaches

— ARIMA.P; ····· ES.P;
- - - PAST.P;

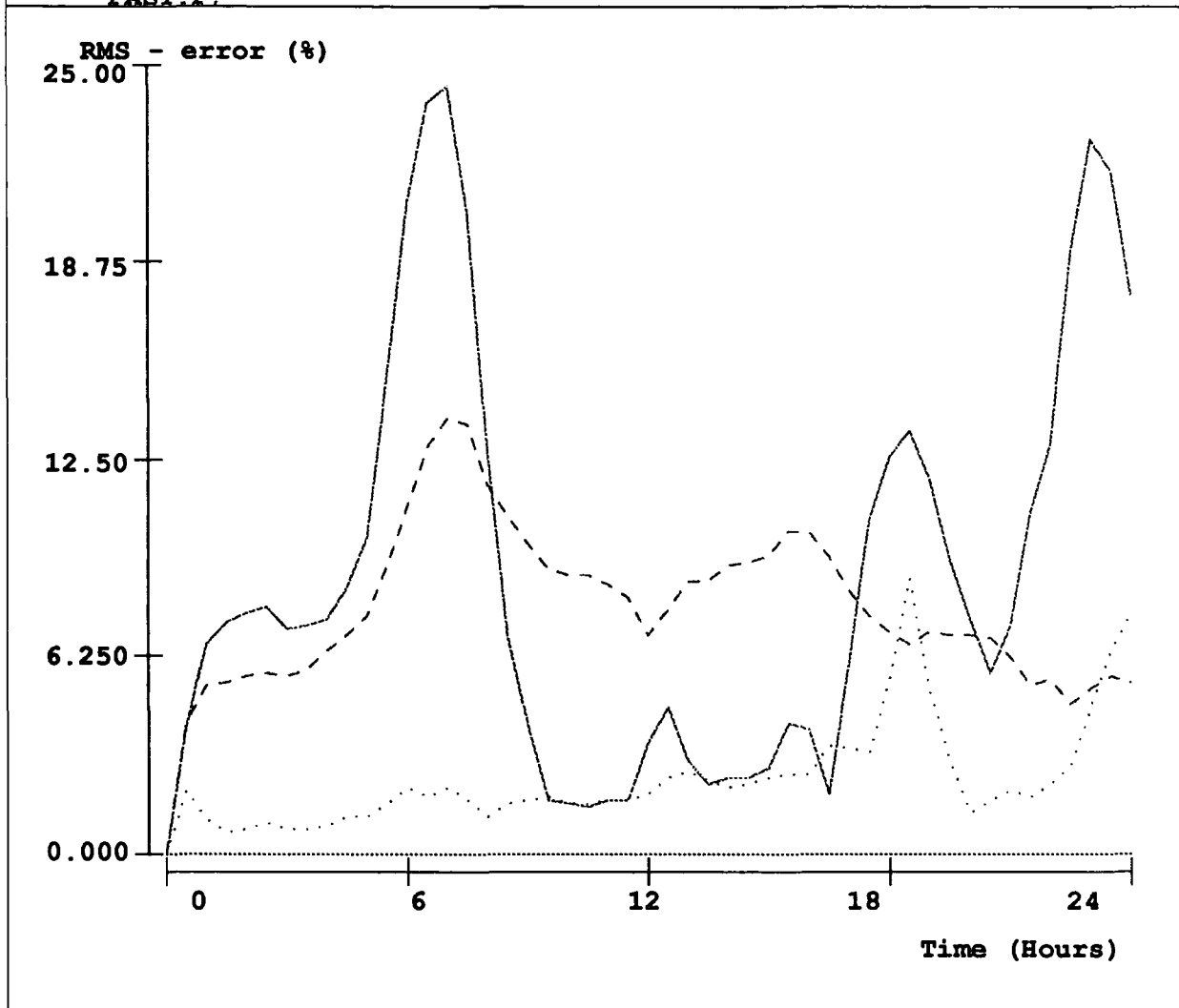


Figure 5.30 Overall Errors by Different Approaches (GMT/BST)

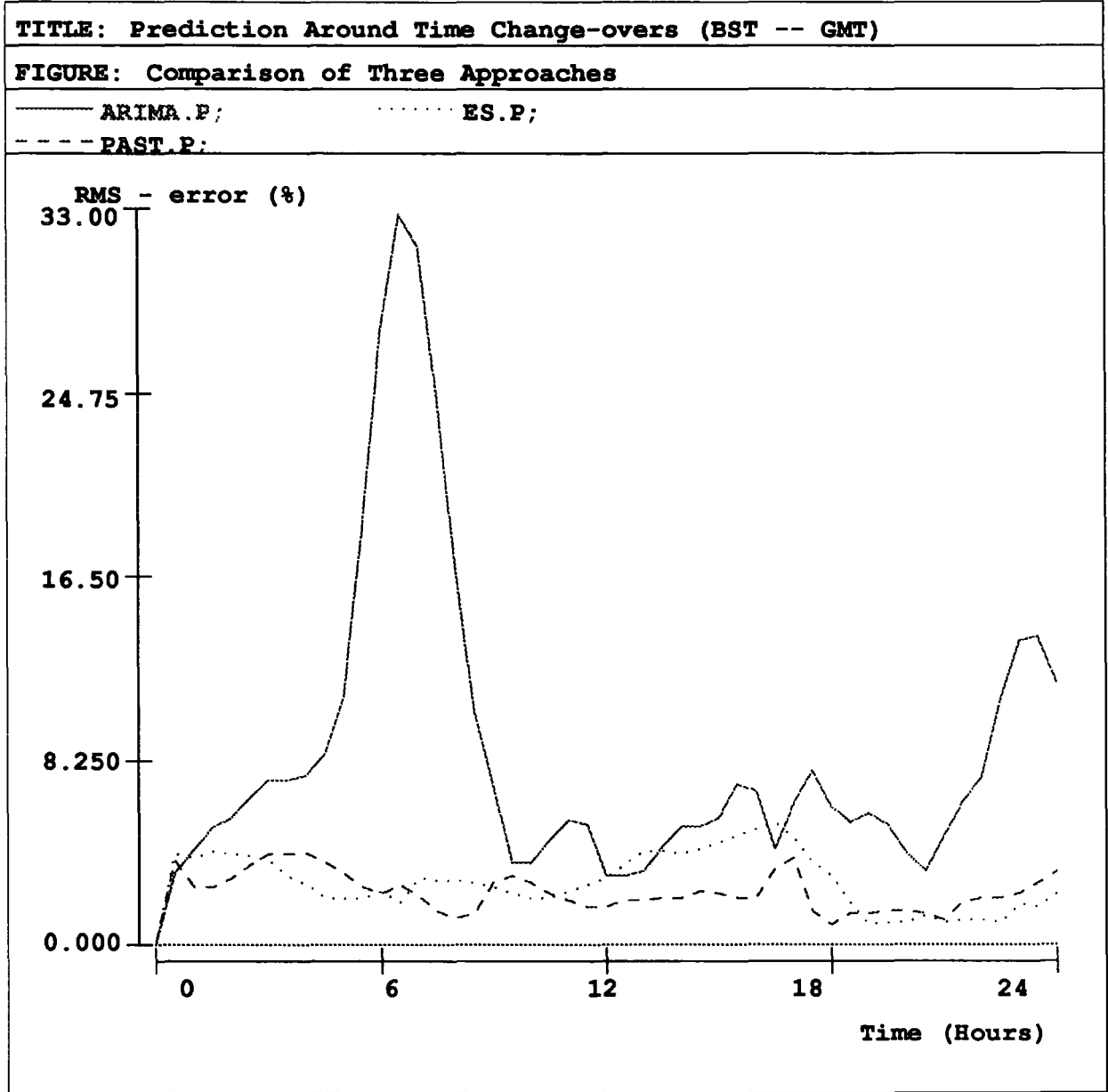


Figure 5.31 Overall Errors by Different Approaches (BST/GMT)

the loads of the same periods of previous years which reflect the load change around time change-overs, so generally speaking, the method can give better results than that only using the loads of last year. However, the expert system approach only uses the loads of current year without the use of previous year's data.

Figures 5.30 and 5.31 represent the comparison of prediction errors over 24 hours by the three methods stated above for the weekdays following the time change-overs when predictions are conducted at midnight. It can be seen from them that the ARIMA model has the worst prediction results. The result produced by the method using the load data of the previous year for prediction of the day following the time change-over from BST to GMT, presents a level of accuracy of almost the same scale as that by the expert system approach. However, because of the possibility of the occurrence of time change-over from GMT to BST at the same period as Easter weekends, the expert system approach has a better performance than the others, although it is not so good at predicting the evening peak loads at which the utilisation is complex.

5.8 Discussion and conclusion

The chapter has presented a new approach to predict loads around time change-overs, which can be compared with the most commonly used Relative Gap method for prediction of special events. As has been discussed in earlier sections, the prediction of electrical demand around time change-overs both from GMT to BST and from BST to GMT is a great difficulty in short-term load forecasting. This is because the load patterns change from week to week, even for the same days-of-week during the period of time change-overs. The reason is that the change-overs alter the consumer's use of electrical power. In other words, some loads which are regulated by nominal clock time are shifted at the change-overs, while those that are governed by independent factors, such as off-peak time-switches and the onset of darkness, are not. The effect of time change-overs on individual components may not be easy to draw up, which makes prediction very difficult.

Time change-overs have a similar effect on the utilisation of electricity from year to year, thus, the relative gaps can be used to predict the loads around the periods by reflecting the load change trend of the same periods in previous years. However, the concurrence of time change-over from GMT to BST with the Easter weekends causes variations. At this point, only the approach of expert systems can find the optimal prediction for this period. This chapter introduces a new approach based on the disaggregated results of chapter 4, which separates the lighting loads from the other loads. The lighting loads are generally governed by the sunset and sunrise time, whilst the rest of the loads are supposed to alter by the time change-overs only. After both loads are predicted, the overall load is obtained with a result that the approach can be comparable with the relative gap approaches. The advantage of the approach is that it does not require the load data of previous year, instead, the sun-set time only.

Weather conditions have an important contribution to the errors. If the weather conditions around the periods of time change-overs change significantly, the weather-dependent loads will vary with the weather changes. The method of expert systems applied here only takes the factor of the lighting-up time into consideration without other weather factors. So, if the relationship between individual components and weather factors is obtained, more accurate prediction will be expected.

CHAPTER 6

LOAD FORECASTING INCLUDING HOLIDAY EFFECTS

6.1 Introduction

The nature of electricity demand, possessing the pronounced daily and weekly periodicity, with only a relatively small variation in the demand shape and level from week to week, makes univariate forecasting an accurate and reliable method for short-term demand prediction. However, this method of prediction for short-term periods does not seem suitable for the prediction of national holidays that repeat themselves only from year to year and, more often, alter both the shape and level of the electrical demand during the period of holidays and a few days before and after. The demand data of this special period will upset prediction even over normal periods if they are used as part of the whole past data set from which modelling and prediction is carried out. These will sufficiently cause forecasting made by using conventional time series methods to be hopelessly inaccurate over these special periods.

Thus, it is necessary to adopt a systematic approach to modify the prediction method over holidays, and to clean up the past demand series to remove the adverse effect of special periods.

The results of disaggregation of loads introduced in chapter 4 may appear insufficient to be directly used to predict holiday loads. The reasons are that the disaggregated results of each component can not be validated because of lack of appropriate data at present and that the behaviour change of each component from normal situation to holiday is not known. Here, a novel approach is presented which can be used to make up that inefficiency in estimation of holiday effects.

This chapter will discuss the difference of loads on holidays from that of normal periods, and propose a new approach which can be applied to predicting holiday loads by reflecting what they were in the past. The knowledge is extracted from load behaviour in the past and represented in production rules. A method to eliminate the influence of holidays on normal periods is also presented. The chapter is arranged as follows: section 6.2 describes the load characteristics of holidays ranging from normal fixed Monday Bank Holidays to special holiday periods between Christmas Day and New Year's Day. In section 6.3, an approach of estimation of holiday load is proposed which adopts the relative gap concepts. Followed by section 6.4 which introduces my method of estimation. In the first part of this section (6.4.1), details are given on the use of preceding weekend loads which are used to determine the level of holiday loads. The second part (6.4.2) shows how the weather information can be applied to improve the prediction of holiday loads. The final part of the section (6.4.3) is my introduction of a method to predict Good Friday loads, which I believe has not yet been touched upon although the problem is there. Efforts are made in section 6.5 to predict loads of special holidays such as Christmas Day, Boxing Day, and New Year's Day. Section 6.6 describes a method of predicting loads of other days between Christmas Day and New Year's Day. Section 6.7 illustrates how effects of these special day loads can be eliminated in order to adopt the usual ARIMA model to predict loads for the following normal periods. Section 6.8 and 6.9 present some knowledge stored in knowledge base and some POP-11 procedures for predicting holiday loads respectively. Finally, a summary is given in section 6.10.

6.2 Characteristics of load over special periods

Electrical demand is greatly affected by such public holidays as Easter, and one-day bank holidays like Summer Bank Holiday. The electrical demand on Monday Bank Holiday is considerably lower (normally by 30 per cent) than on normal Mondays. Figure 6.1 shows three Monday load curves around the Spring Bank Holiday. The reason is that some industrial load is shut down and commercial load reduced (see curve III in Figure 6.1) during the holidays.

In England and Wales, bank holidays are usually on Mondays (which are referred to as normal holidays in later sections, while New Year' Day, Good Friday and Christmas Day are separately dealt with as special holidays). The holiday effects also impinge on the neighbouring days. Although there are at present only eight time-tabled bank holidays each year, the total number of days that present abnormal demand behaviour can amount to about thirty, with those days affected before and after the holidays included [196].

The difference of loads between Monday Bank Holiday and normal Mondays is not only in the level, but also in the shape (see Figure 6.1). During the public holidays, some commercial loads and the industrial loads decrease. The pattern on Monday Bank Holidays, however, is more or less like that on weekends (see Figure 6.2), although some particular days, Good Friday for example, have Saturday characteristics. From the following week onwards, the same day-of-week (Monday) load will be back to normal behaviour (see also Figure 6.1: curve I is the Monday load before the holiday week, curve II is the Monday load after the holiday week).

It is also found that the patterns of load are also different from one public holiday to another. An example of this characteristic is shown in Figure 6.3 which compares the loads of Spring Bank Holiday with that of the Summer Bank Holiday in 1984. The solid curve indicates the Spring Bank Holiday in 1984 and the dashed one for the Summer Bank Holiday. Although, in the figure, the evening peak loads are on about the same time and with the similar levels, the morning peak loads are totally different. The morning peak load of spring bank holiday is about 10% higher and appears much later than that of summer bank holiday.

Load of special holiday periods between Christmas Day and New Year's Day have different characteristics from that of the fixed Monday Bank Holidays. They also change from year to year (see Figure 6.4). It seems that it is extremely difficult to predict load around this period.

TITLE: Holiday Effects

FIGURE: Pre, Post Holiday Monday with Bank Holiday Monday

—— PRE BANK.P; POST_BANK.P;
- - - - SPRING BANK.P;

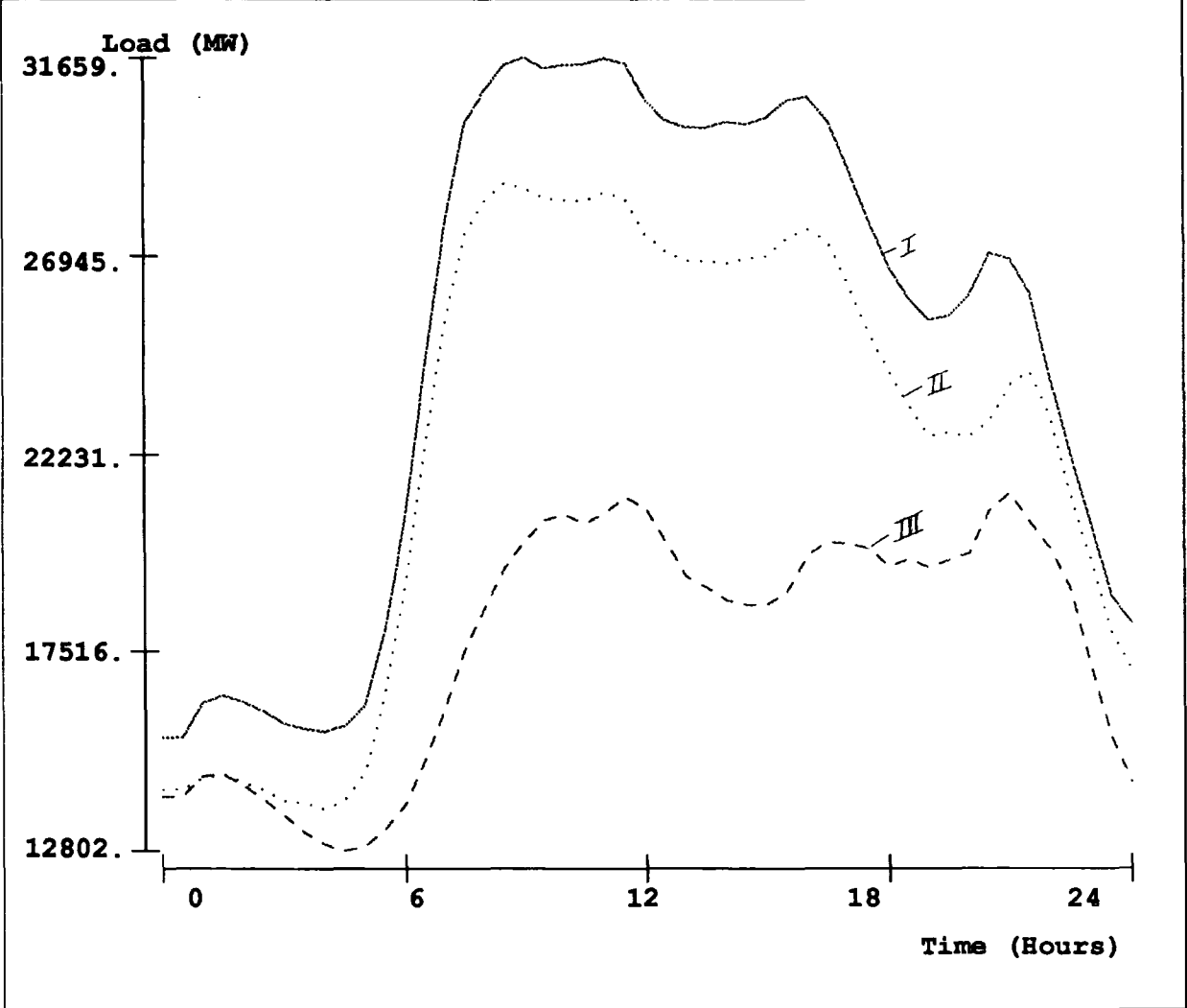


Figure 6.1 Effects of Public Holidays

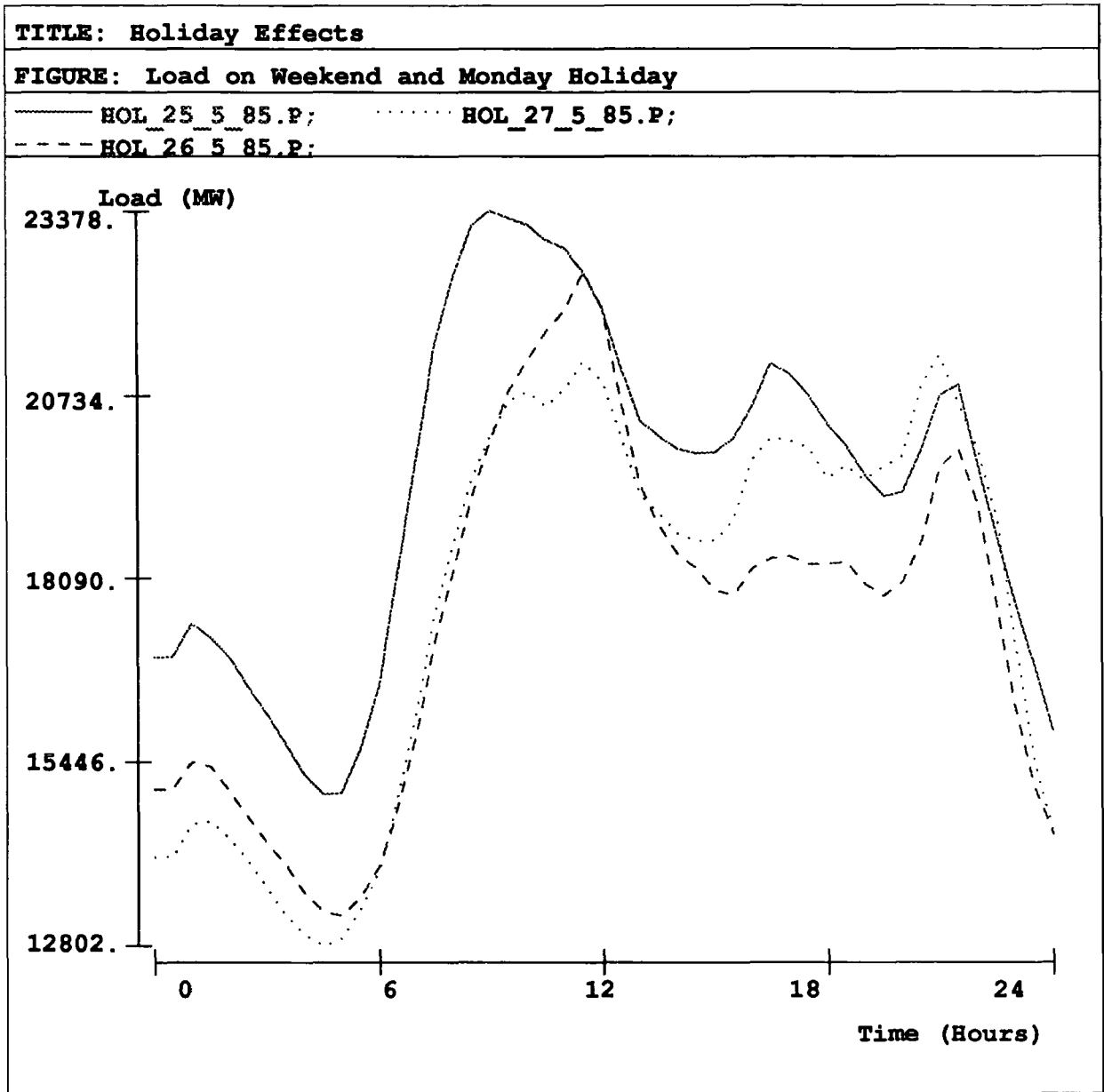


Figure 6.2 Load Behaviour on Weekends and Monday Bank Holiday

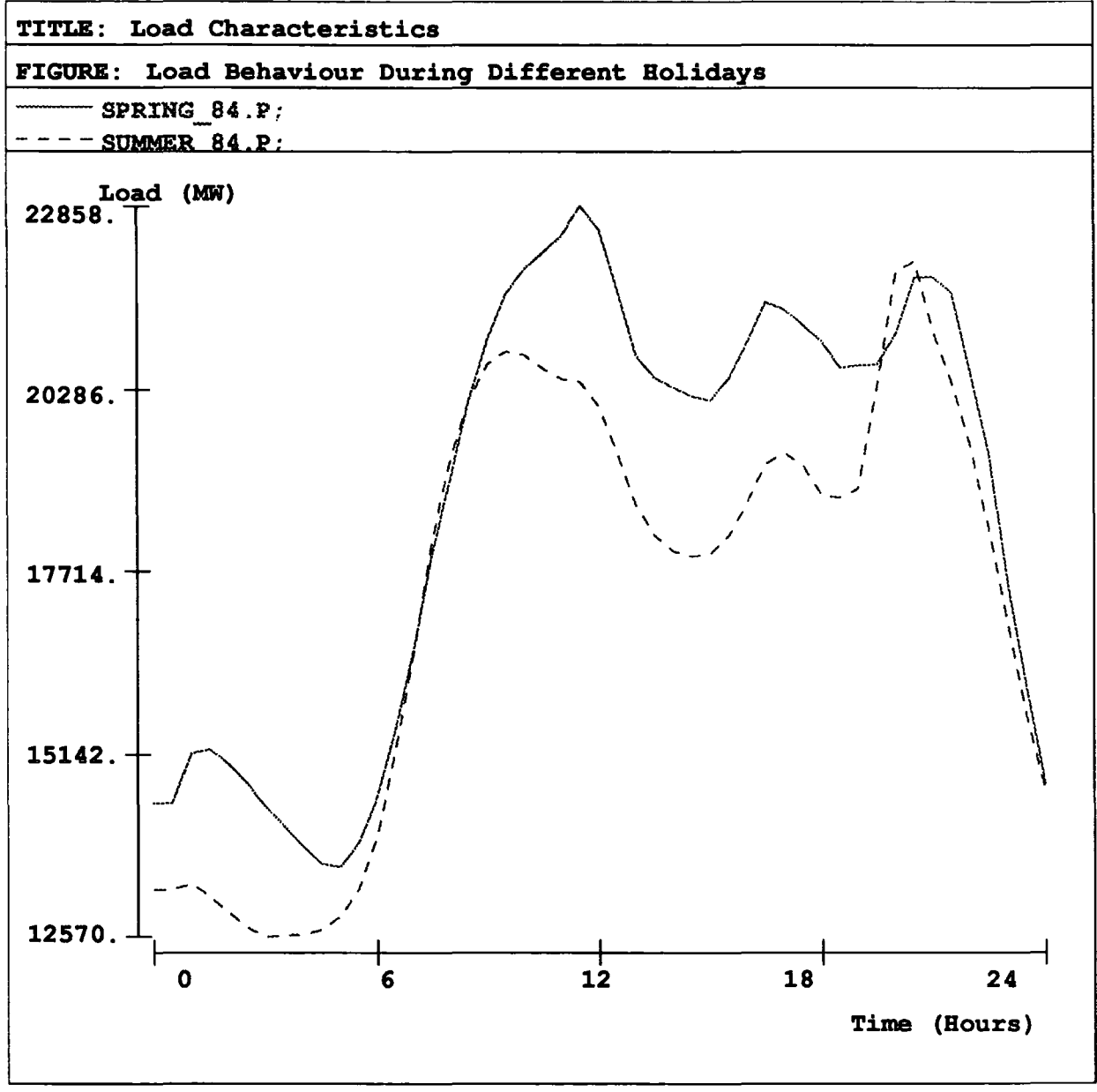


Figure 6.3 Loads of Different Public Holidays

TITLE: Load Characteristics

FIGURE: Load Behaviour Between Christmas Day and New Year's Day

—— Load 83.dat

---- Load 84.dat

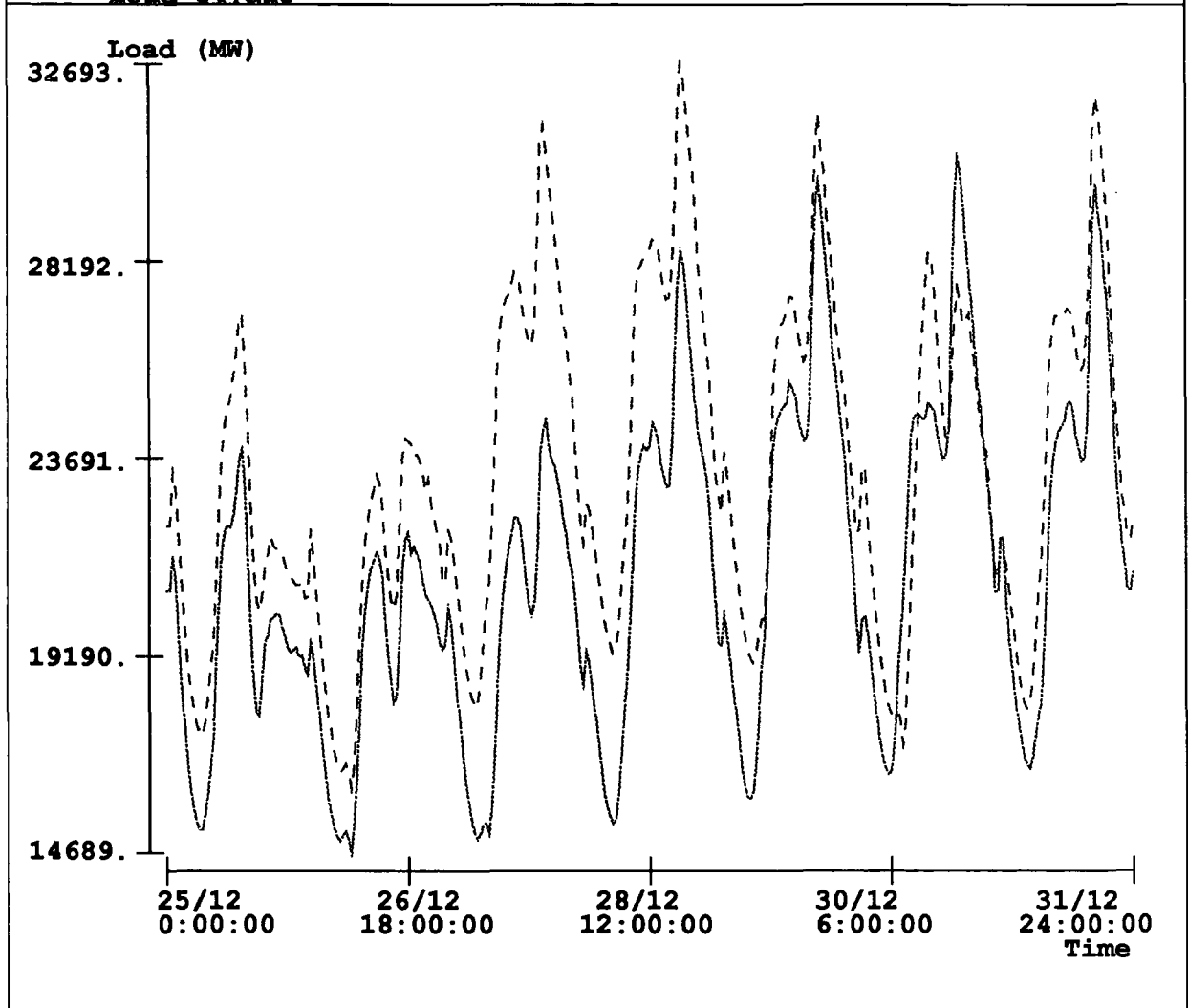


Figure 6.4 Load Behaviour Between Christmas Day and New Year's Day

TITLE: Load Characteristics

FIGURE: Summer Bank Holidays for 1983 & 1984

— SUMMER 83.P;

- - - SUMMER 84.P;

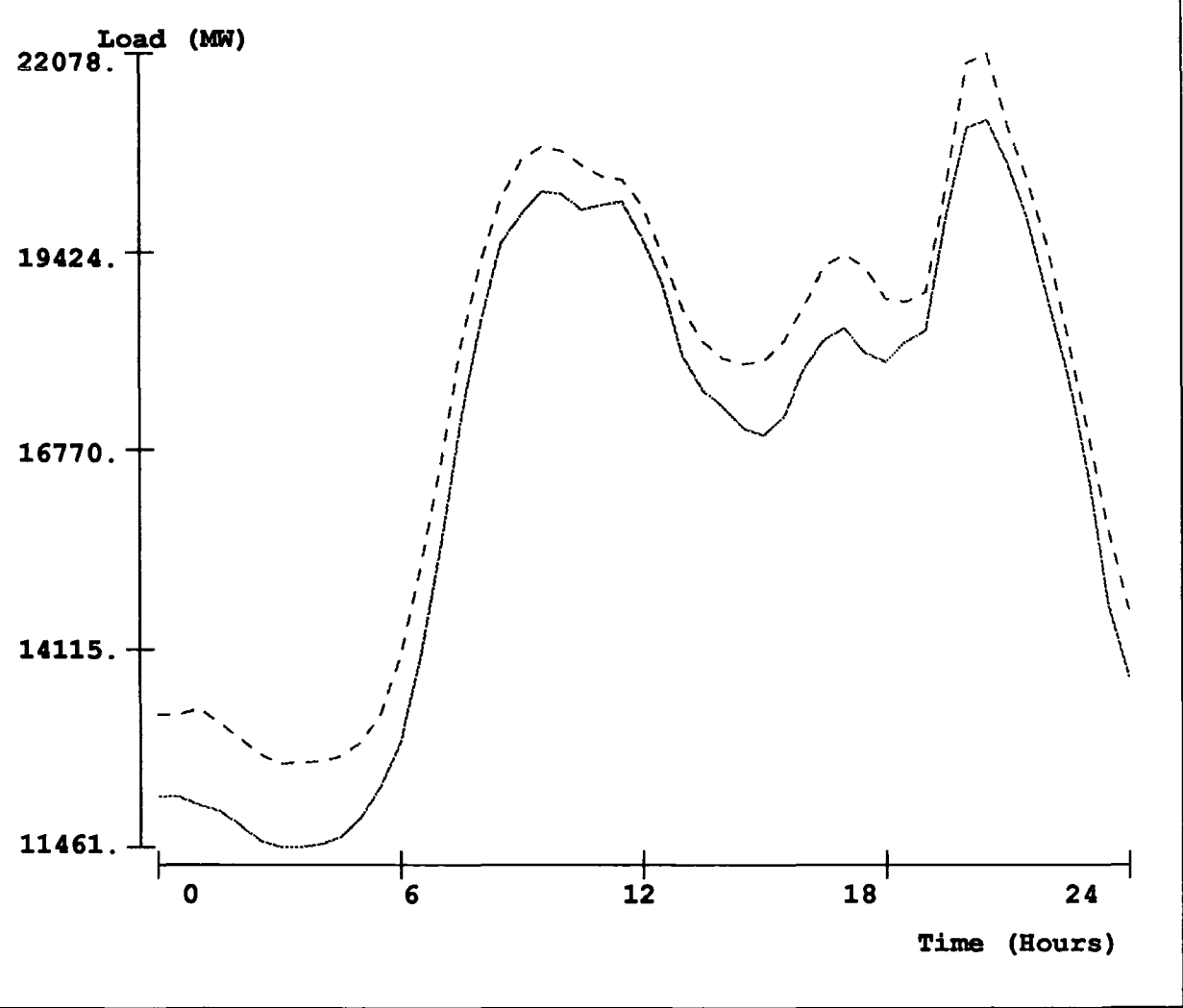


Figure 6.5 Similarity of Load for Same Public Holiday Each Year

Estimation of loads for special days is difficult for an algorithmic method because there is a complexity of factors which affect load pattern and the factors themselves are not precise. Even if all factors are known, the effect of a certain factor is not regular. Based on the characteristics observed, a new approach is proposed as follows.

6.3 Prediction by factoring the results of ARIMA

Loads of public holidays can not be predicted by the conventional time series, due to the lack of repetition in the period of modelling and predicting. However, from year to year, for the same kind of holiday, the load changes in a similar way (see Figure 6.5). The solid curve in Figure 6.5 depicts the summer bank holiday in 1983 and the dashed one for that in 1984. The similarity is obvious. It is true that the same holiday occurs within one week difference and in the same season, from year to year (except Easter holiday the date of which may vary by one month either in March or in April). And, normally, the weather conditions do not change dramatically and consumer's use of electricity is more or less the same.

Based on this observation, holiday effects can be predicted through observing what they were like in the past. Meslier [94] used ARIMA method of model $(1, 0, 0) \times (0, 1, 1)_7 \times (0, 1, 1)_{365}$ to forecast daily energy consumption one day ahead. His model might be good at forecasting loads for the holidays such as New Year's Day, Christmas Day, and Boxing Day, because the periodicity for them is exactly 365 days. But it will not work for other public holidays in Britain as the dates of holidays change from year to year. In addition, the model has as many as 138 parameters.

The use of Relative Gaps (R. G.) can be introduced [160], considering the characteristics of similarity of load changing. The first kind of Relative Gap (indicated as R. G. 1) has been defined as in earlier chapter as in (6.1) as the load difference between the actual load and the predicted load for the holiday:

$$R.G.1(D, t) = Load_a(D, t) - Load_p(D, t) \quad (6.1)$$

where $Load_a$ and $Load_p$ are the actual and predicted loads for day D at time t respectively. $Load_p$ is predicted from the model which assumes that the day D is a normal day with normal loads.

The second kind of Relative Gap (indicated as R. G. 2) has been defined in (6.2) as the load difference between the actual load and the predicted load in percentage of normal load:

$$R.G.2(D, t) = \frac{Load_a(D, t) - Load_p(D, t)}{Load_p(D, t)} \quad (6.2)$$

In order to predict the holiday loads for the current year, the current R. G. 1 and R. G. 2 should be obtained in the first instance, if it is assumed that the current year's R. G. 1 and R. G. 2 remain the same as that of the previous years. They can be calculated by applying the above equations with the data of the previous years. Then, the estimation of the current holiday loads can be carried on by the following formulae:

$$Load_a(D, t) = R.G.1(D, t) + Load_p(D, t) \quad (6.3)$$

$$Load_a(D, t) = R.G.2(D, t) * Load_p(D, t) + Load_p(D, t) \quad (6.4)$$

Based on the R. G. 1 and R. G. 2 estimated from loads of previous years, the prediction results are compared in Table 6.1 for some bank holidays of the CEGB system load in 1985. The results seem encouraging when compared with that of the original ARIMA model.

**Table 6.1: Results of Predicting Load for Fixed Bank Holidays
by R. G. 1 and R. G. 2 (1985)**

Date	Original ARIMA (%)		R. G. 1 (%)		R. G. 2 (%)	
	R.M.S.	Max	R.M.S	Max	R.M.S.	Max
5/4/1985	22.02	33.41	12.9	35.18	10.42	27.62
8/4/1985	35.14	59.53	4.92	-9.87	7.77	-14.91
6/5/1985	33.70	54.34	10.89	19.19	8.65	16.78
27/5/1985	38.76	65.31	5.65	11.25	5.51	10.42
26/8/1985	28.17	46.87	1.87	4.04	1.35	-3.41

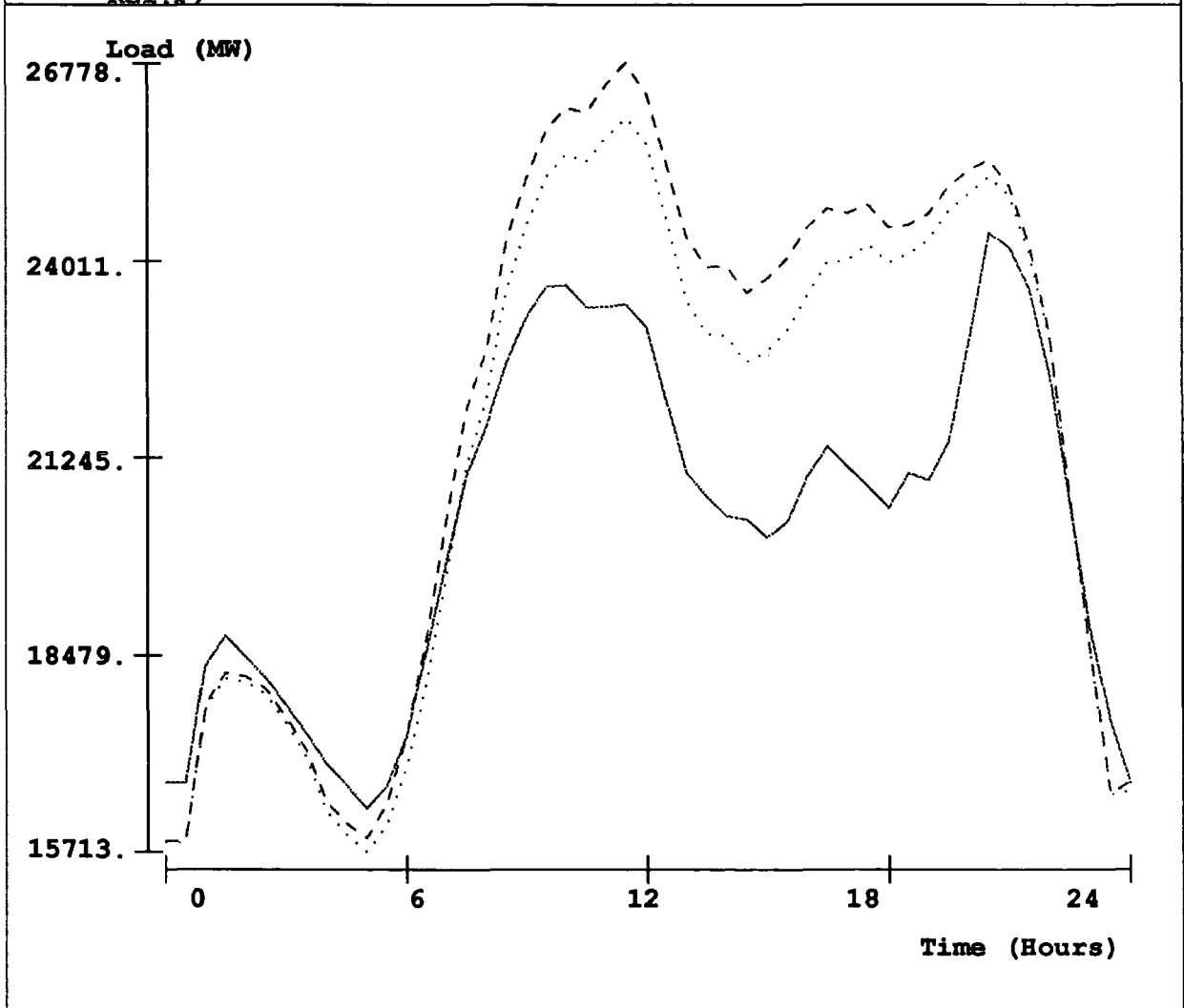
It can be seen from the table that the original ARIMA model gave unacceptably large forecasting errors with R.M.S. error of 38.76 per cent and the maximum error of 65.31 per cent. The reason is that the original ARIMA method only lies on the daily and weekly periodicities of the actual past load data to fit the model. Since all the days in the past are all normal working days, therefore, the loads are high. However, when the fitted model is utilised to predict the load for the public holiday, the predicted load must be much higher than the actual load recorded for the holiday, as shown in Figure 6.1. Although the results of R.G.s are much better compared with that of the ARIMA model, the accuracy is still too big to be acceptable for on-line operation. It is easy to understand the large errors from the results by R. G. 1, which uses the load difference as the reference. The overall load keeps increasing over time because of the growth of industrial production and other economic development factors. Also different components of the overall load do not increase at the same pace. Therefore, R. G. 1 will not keep constant from year to year. For the same reason, the results made by R. G. 2 are also disappointing.

An example of predicting loads for May-day of 1985 is shown in Figure 6.6, where the actual loads are contrasted with the two predictions made by R. G. 1 and R. G. 2. The predicted loads depicted by Figure 6.6, obtained

TITLE: Load Prediction for Holidays

FIGURE: By Relative Gaps

—— ACT.P; ····· RG2.P;
- - - - RG1.P;



**Figure 6.6 Load Prediction for May-day (1985)
by R. G. 1 and R. G. 2**

by R. G. 1 or by R. G. 2, are much higher than the actual loads, especially around the morning peak time. The following possible reasons may be the causes of this phenomenon. One is that the base load in the present year is too high, which results in the high prediction of loads $Load_p$. The other is that the actual loads in the previous year are too high probably as a result of bad weather conditions. So, it might be better to introduce some factors which can somehow indicate the level in which the holiday loads are located. Such a novel approach is proposed in the following section.

6.4 Prediction by referring to preceding weekends

As has been described earlier, the loads on normal holidays are more or less the same as they are on the preceding weekends. So, the loads of the weekends which are preceding the holiday may be used to estimate the level of holiday loads. The relationship between the holiday loads and that of the preceding weekends can be estimated by the past data.

6.4.1 Predicting holidays by past data

During the holiday, as is known, the industrial loads shut down, as on a Sunday. But the pattern of the commercial load does not exactly resemble the Saturday pattern, since the banks are closed on holidays; nor the Sunday pattern, because some shops are open on some holidays. Therefore, it may not be suitable to predict the holiday effect just on the basis of Saturday or Sunday patterns. Nevertheless, the loads on the regular public holidays, for example Spring Bank Holiday, are of the same level, and the load shapes are the same in successive years.

Based upon this observation, we can estimate the holiday effects by taking the average of Saturday and Sunday load patterns in the following way:

For a given Monday Bank Holiday, the overall load of the holiday can be factorised by that of the previous Saturday and Sunday. It is expressed by the following equations:

$$f_{sat}(t) = \frac{L_{hol}(t)}{L_{sat}(t)} \quad (6.5)$$

$$f_{sun}(t) = \frac{L_{hol}(t)}{L_{sun}(t)} \quad (6.6)$$

where parameters $f_{sat}(t)$ and $f_{sun}(t)$ indicate the weights of overall loads of holiday on that of Saturday, Sunday at time t respectively; For a whole day, f is a list of 48 elements (half-hourly).

The parameters f reflect the load change trend from weekends (Saturday, Sunday) to the holiday. Actually we can see from the past data that the f s are similar both in shapes and levels from year to year. If the f s are assumed to keep the same value from year to year, i.e., the overall load change from the preceding weekends to the holiday follows the same trend in successive years. Then, the loads of the holiday in year y_2 can be calculated on the basis of loads of the preceding weekends and that during the holiday period in year y_1 :

$$L_{hol-sat}(y_2, t) = \frac{L_{sat}(y_2, t)}{L_{sat}(y_1, t)} * L_{hol}(y_1, t) \quad (6.7)$$

$$L_{hol-sun}(y_2, t) = \frac{L_{sun}(y_2, t)}{L_{sun}(y_1, t)} * L_{hol}(y_1, t) \quad (6.8)$$

where $L_{hol-sat}(y_2, t)$ and $L_{hol-sun}(y_2, t)$ are the estimation of holiday loads by the loads of preceding Saturday and Sunday respectively. Each of them, of course, can be used to approximate the holiday loads.

However, in order to have the best estimation of holiday loads, the best combination of results from Saturday and Sunday may be obtained by the coefficients of f_1 and f_2 :

$$L_{hol} = f_1 * L_{hol-sat} + f_2 * L_{hol-sun} \quad (6.9)$$

where parameters f_1 and f_2 are the weights of $L_{hol-sat}$ and $L_{hol-sun}$ on the L_{hol} respectively.

Since the holiday loads are in the level of that on the weekends, the relationship between f_1 and f_2 can be constrained as:

$$f_1 + f_2 = 1.0 \quad (6.10)$$

The parameters f_1 and f_2 can be easily estimated on the data of two earlier years.

Therefore, the load of the holiday can be predicted on the assumption that f_1 and f_2 do not change for the same holiday in successive years.

Figure 6.7 shows an example of predicting the load for the Summer Bank Holiday in 1985. The results for different Monday Bank Holidays are listed in Table 6.2.

It can be seen from Table 6.2 that the errors (R.M.S.) in predicting May-Day loads by any approach were very high. The reason was possibly the effect of weather not being included. In the spring, the weather changes rapidly, and the weather conditions of May-Days may be different from year to year. The results of prediction for the Summer Bank Holiday, however, were extremely accurate. The reason was possibly the converse of the above, because the weather conditions both in 1984 and in 1985 were quite similar.

TITLE: Holiday Effects

FIGURE: Comparison of Predicted Load with Actual Load

----- PRED 26_8_85.P;

----- ACT 26_8_85.P;

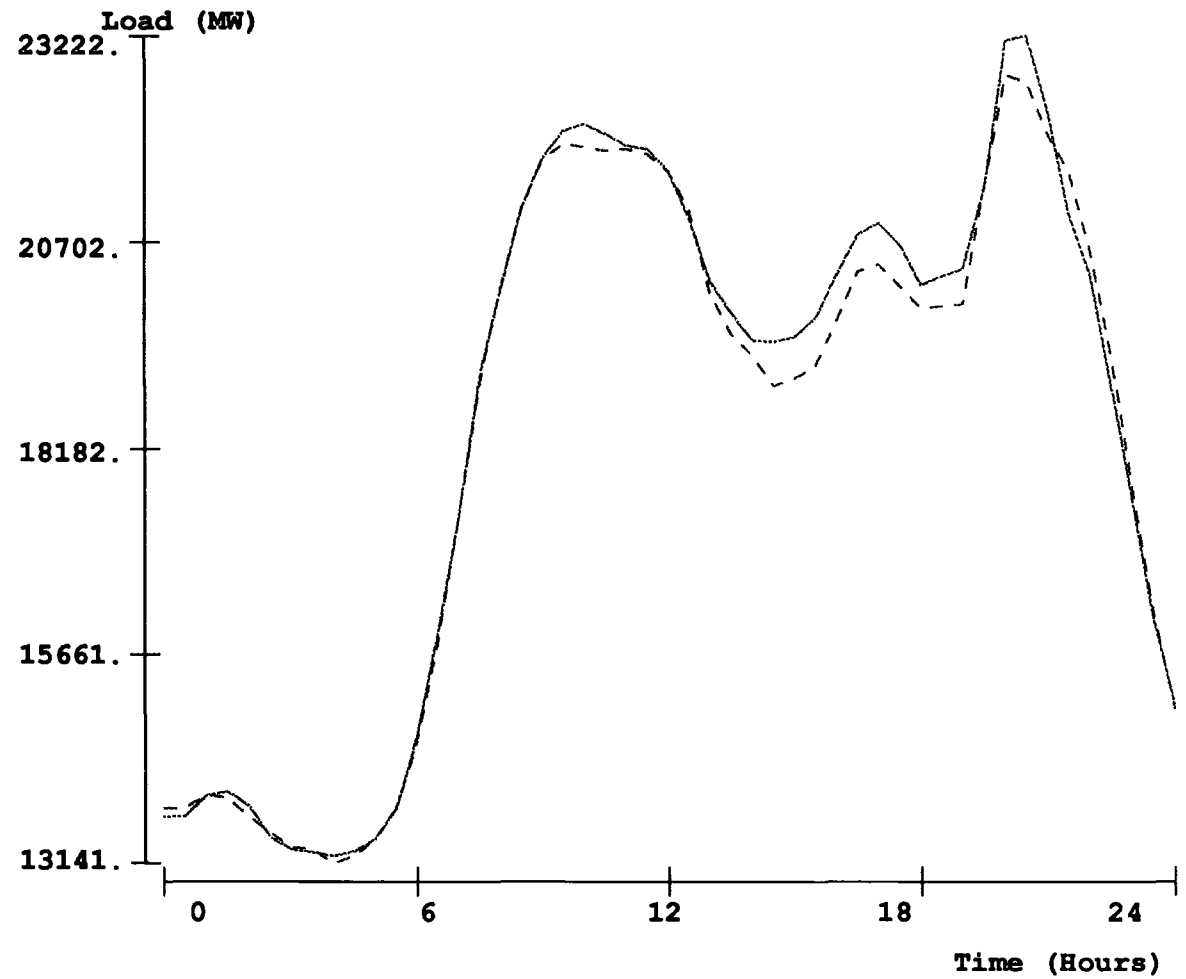


Figure 6.7 Results for Summer Bank Holiday (1985)

**Table 6.2: Comparison of Prediction by Different Approaches
(Lead Time = 24 Hours)**

Approach	Error (%)	Easter-Monday	Summer-bank	May-day	Spring-bank
1	R.M.S.	35.14	28.17	33.70	38.76
	M.A.P.	30.86	23.97	28.46	33.84
	Max.	59.53	46.87	54.34	65.31
2	R.M.S.	4.92	1.87	10.89	5.65
	M.A.P.	4.04	1.42	8.62	4.85
	Max.	-9.87	4.31	19.19	11.25
3	R.M.S.	7.77	1.35	8.65	5.51
	M.A.P.	6.44	1.13	7.00	4.82
	Max.	-14.91	-3.41	16.78	10.42
4	R.M.S.	3.04	1.40	5.79	3.93
	M.A.P.	2.62	1.05	5.30	3.27
	Max.	-5.84	3.00	9.71	-7.85
	f_1	0.5	0.5	0.2	0.2
	f_2	0.5	0.5	0.8	0.8
5	M.A.P.	6.79	2.44		
	Max.	13.6	-6.6		

Notes:

R.M.S. Error: root mean squared error;

M.A.P. Error: mean of absolute error in percentage;

Max. Error: maximum absolute error.

Approach 1: the original ARIMA;

Approach 2: ARIMA with R. G. 1;

Approach 3: ARIMA with R. G. 2;

Approach 4: estimation based on the earlier weekends;

Approach 5: modified ARIMA by Smith.

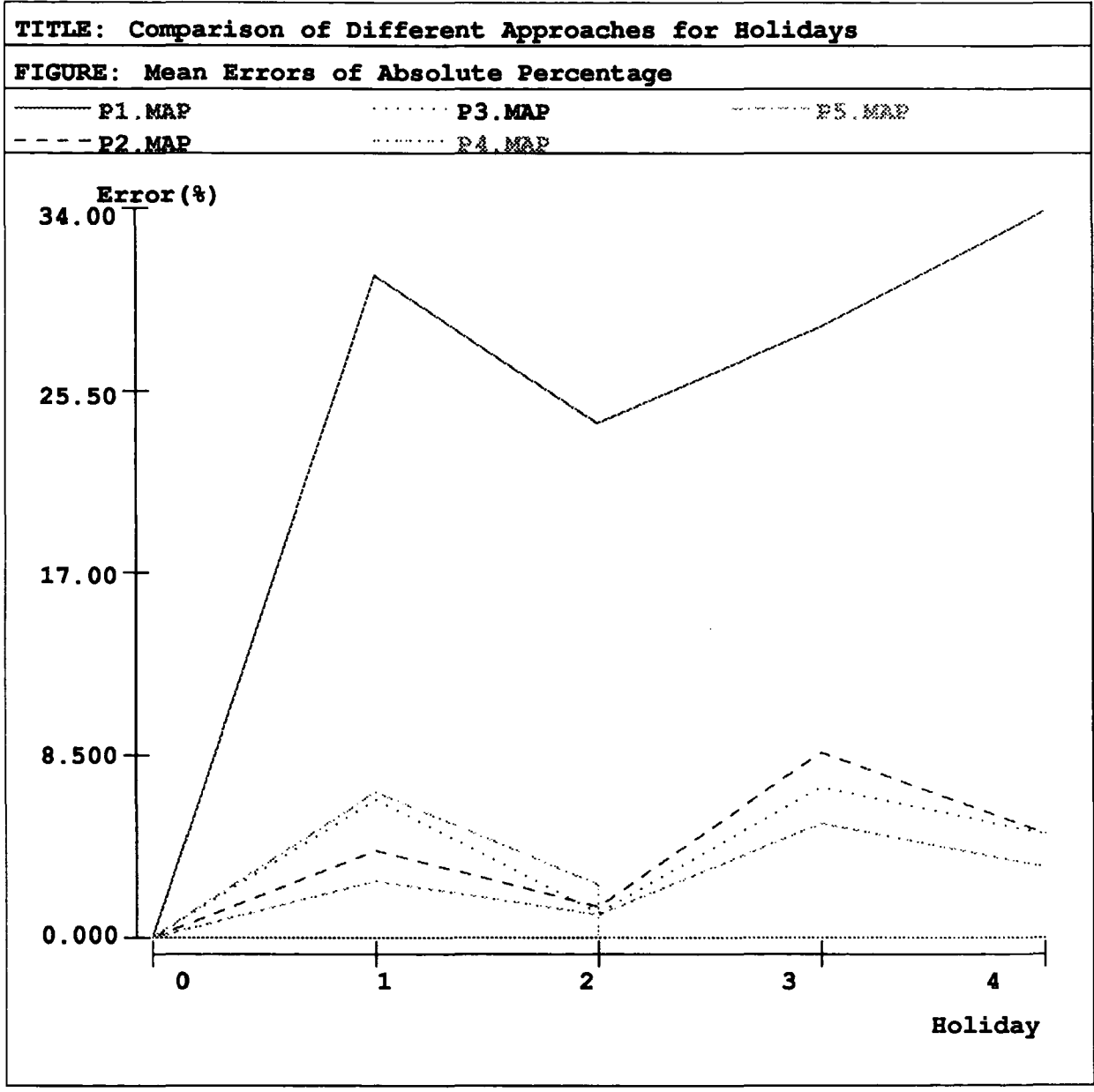


Figure 6.8 R.M.S. Errors of Different Approaches for Holidays

1: Easter Monday; 2: Summer Bank Holiday;
 3: May Day; 4: Spring Bank Holiday.

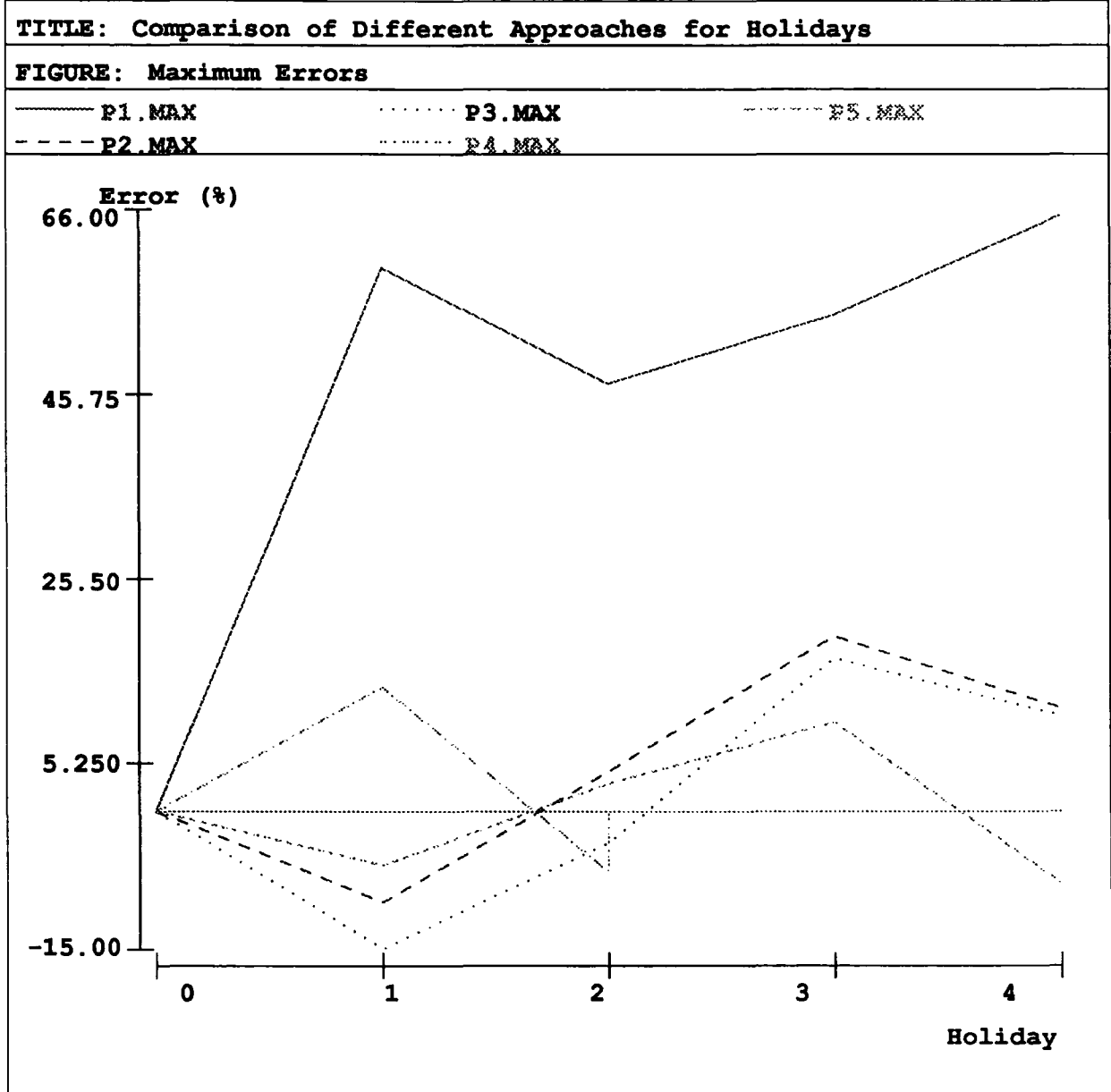


Figure 6.9 Maximum Errors of Different Approaches for Holidays

- 1: Easter Monday; 2: Summer Bank Holiday;
- 3: May Day; 4: Spring Bank Holiday.

The results are also compared with that of Smith's method [196] in Table 6.2. He used the Special Period Demand Shortfall (SPDS, as Relative Gap) as a intrinsic value to each Bank Holiday period, i.e., for a particular Bank Holiday period: SPDS is expected to be similar for the following year.

It can be seen from Table 6.2 that the use of Relative Gaps (including Smith's) can improve the accuracy over the original ARIMA. But the results are still far away from that predicted by the approach proposed in this section. The key difference between them is that the Relative Gaps are the differences between the loads of holidays and that of normal periods, while the proposed approach is to use the earlier weekends as the reference. Because the holidays are regarded more or less as an extension of their weekends for consumers and the amount of their electrical demand on the holidays will not be very much different from that on weekends. With this in consideration, the weekend loads are then taken as reference for prediction in this approach.

6.4.2 Including weather effects on holidays

Load prediction for public holidays, so far, only takes the characteristics of past data, i.e., only reflecting what they were in the past. As weather conditions have effects on consumers' use of electricity, they will have great influence on the national holiday load as well. Because during the holiday, the industrial load shuts down, the main proportion of the overall loads is the domestic load and commercial load which are considerably affected by the weather condition changes.

The proposed estimation method is based on the weekend loads preceding the holiday, which are also greatly influenced by the weather conditions.

Based on the earlier estimation for holiday loads, weather effects are calculated in the following ways.

First, the weather-sensitive part of the overall load on the past weekends is adjusted by their weather factors. Only maximum temperature is used,

in order that the weather-dependent loads correspond to the same weather conditions of the past holiday. The load/temperature rate is based on the load changes from the earlier weekends to this weekends. Saturdays and Sundays are separately considered, because their load characteristics are different from one another.

Second, the same approximation method, as used in the earlier section, is used to determine the Saturday and Sunday weight on the holiday for previous years. After this is done, the preceding Saturday and Sunday loads of the current year are adjusted as well in order that the weather conditions on both days tone in with that of the predicted holiday. Finally, the holiday loads are estimated on the basis of the adjusted Saturday and Sunday loads.

Table 6.3: Results of Prediction with Weather Considered for Public Holidays (1985)

Approach	Errors (%)	Easter-Monday	Summer-bank	May-day	Spring-bank
Without Weather Considered	R.M.S.	3.04	1.40	5.79	3.93
	Max.	-5.84	3.00	9.71	-7.85
	M.A.P.	2.62	1.05	5.30	3.27
	Coefficients				
	$f_{sat.}$	0.5	0.5	0.2	0.2
	$f_{sun.}$	0.5	0.5	0.8	0.8
With Weather Considered	R.M.S.	2.51	1.40	5.64	3.60
	Max.	-4.73	3.00	9.28	-7.85
	M.A.P.	2.17	1.05	5.13	2.79
	Coefficients				
	$f_{sat.}$	0.37	0.5	0.2	0.2
	$f_{sun.}$	0.63	0.5	0.8	0.8

The results of such an approach are listed in Table 6.3. A comparison of prediction results of with and without weather consideration is shown in Figure 6.10.

From Table 6.3 and Figure 6.10, it can be concluded that the prediction with weather considered performs better than that without the consideration of weather. This shows that the holiday loads are quite sensitive to the weather changes. The results for predicting the Summer Bank Holiday loads indicates that the weather condition of the holiday were similar to that in previous years, and of the preceding weekends.

In conclusion, the proposed method can be used to predict normal Monday Bank Holiday load. The prediction accuracy can be improved by taking weather effects into consideration.

6.4.3 Load prediction for Good Friday

The method proposed in previous sections is based on the preceding weekend loads and the holiday loads in previous years. The reason is that Monday Bank Holidays can be regarded as the extension of weekends. Prediction of loads for Good Friday, however, is different, because the load pattern of Good Friday has the characteristics of Saturday loads. It has been proved infeasible in Table 6.1 to predict such loads even by modified ARIMA models either by R. G. 1 or by R. G. 2. A simple way of estimation would be to use a similar approach to that of Monday Bank Holidays. Instead of using the loads of the preceding weekends as the reference, the preceding Thursday loads are used as the reference for Good Friday.

Weather effects on loads are also approximated for Good Friday in a similar way as in section 6.4.2. The results of testing are listed in Table 6.4. Figure 6.11 shows one of the results.

TITLE: Prediction of Holiday Loads (Easter - Monday)

FIGURE: Comparison of Prediction with & Without Weather Consideration

——— With-Weather ····· Without-Weather
- - - - Act-Load

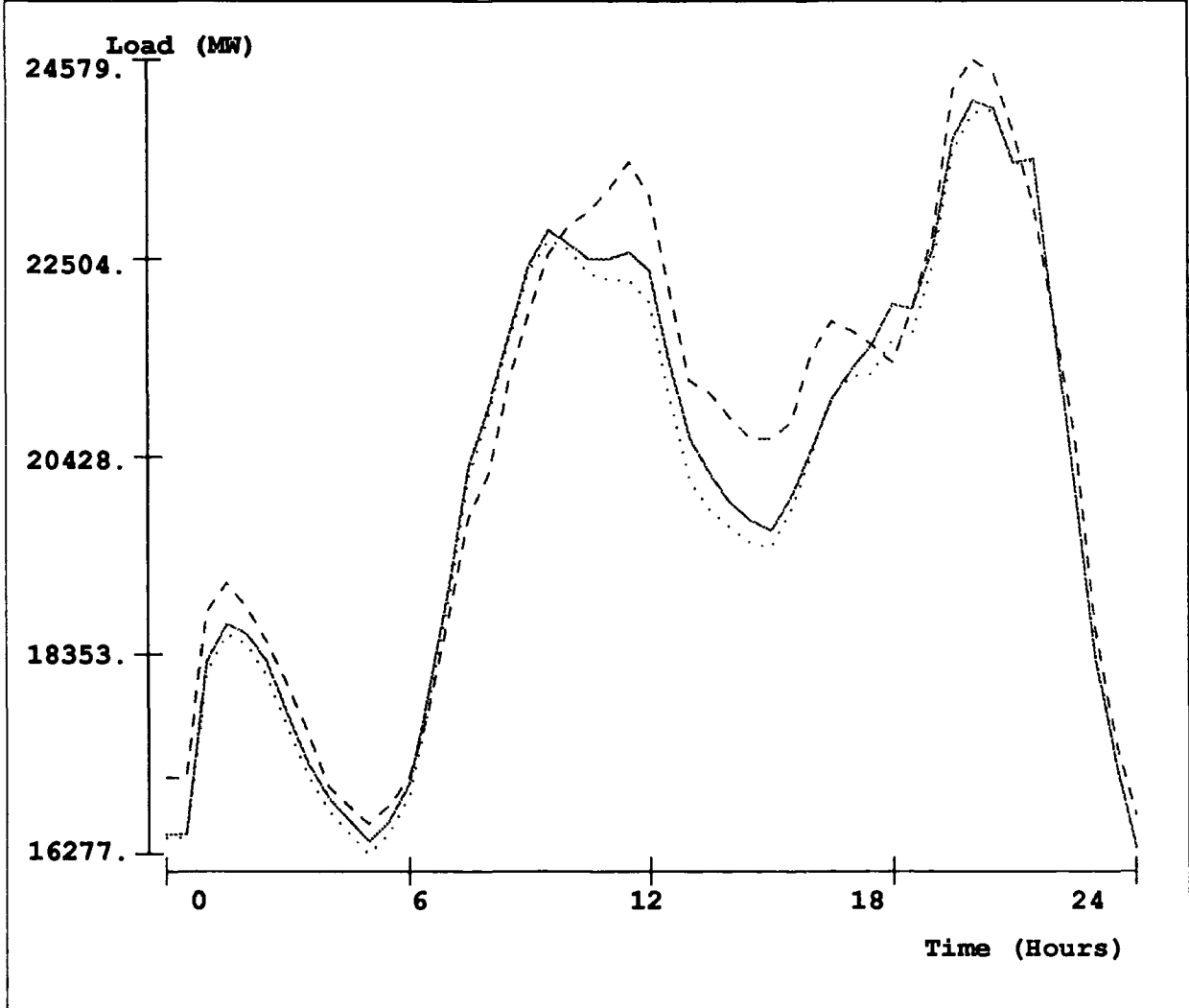


Figure 6.10 Prediction with and Without Weather Consideration

TITLE: Load Prediction for Special Holidays

FIGURE: Prediction for Good Friday (1985)

— Prediction

- - - Act

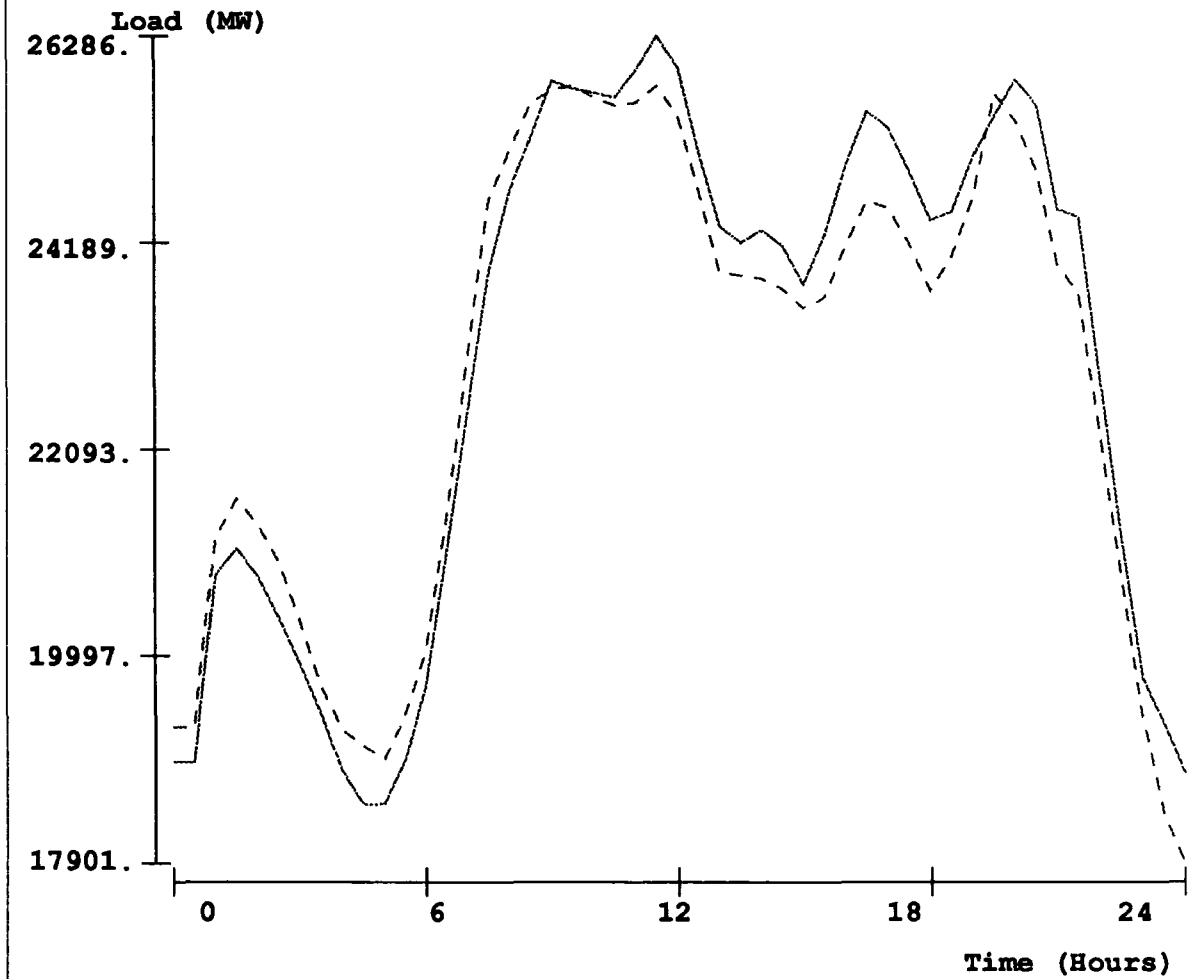


Figure 6.11 Prediction of Loads for Good Friday

Table 6.4: Results of Prediction for Good Friday

Years of Past Good Friday	Weather Condition Considered	Errors (%)		
		R.M.S.	M.A.P.	Max.
1	No	2.96	2.71	-5.39
1	Yes	2.64	2.26	-5.39
2	No	2.43	2.24	5.02
2	Yes	2.37	2.14	5.02

By this example, we can conclude that more past data available will lead to better prediction results, and the method with weather condition being considered certainly proves sounder than that without the consideration of weather conditions.

6.5 Predicting loads of special holidays

The greatest difficulty in predicting holiday load, so far, is to deal with the cases such as Christmas Day, Boxing Day, and New Year's Day, as they occur on a different day-of-week each year, unlike the ordinary Monday Bank Holidays. During these holidays, the load patterns do not resemble any weekend load profiles as the loads on ordinary holidays do. During these holidays, industrial loads behave differently according to what day-of-week the holiday is. However, it is found that the overall load shape on the same type of holidays of each year is very similar, i.e., little variation with days-of-week, although the magnitude was not the same when they occur on a different day-of-week. A weekday Christmas Day obviously demands more load than a weekend Christmas Day. This is because all the parts, except the industrial part which decreases from weekday to weekend, repeat themselves from year to year for the same type of holiday. Therefore, it is possible to use some modification factors to transfer the holidays effect from weekends to weekdays. That means if the holiday occurs on a weekday, no modification is needed,

or say, the modification factor is 1.0. If the holiday occurs on a weekend, modification factor which is greater than 1.0 is required. Different factors are required for Saturday and Sunday. After the factor is considered, the load will be at the same level for the same type of holiday. Different factors for different days-of-week are listed in Table 6.5.

**Table 6.5: Daily Holiday Correction Factors
for Special Holidays**

Day type	X-max day:	Boxing day:	New Year's Day:
Monday	1.0	1.10	1.0
Saturday	1.05	1.10	1.10
Sunday	1.10	1.10	1.10
Others	1.0	1.0	1.0

Table 6.6: Results of Prediction for Christmas Day

Using data	Errors of Prediction (%)					
	1983			1984		
	R.M.S.	M.A.P.	Max.	R.M.S.	M.A.P.	Max.
1982	2.31	1.97	-4.82			
1983				2.46	2.16	-4.50
1982 & 1983				1.89	1.56	-3.34

Table 6.7: Results of Prediction for Boxing Day

Using data	Errors of Prediction (%)					
	1983			1984		
	R.M.S.	M.A.P.	Max.	R.M.S.	M.A.P.	Max.
1982	2.85	2.21	6.36			
1983				1.61	1.36	-3.15
1982 & 1983				2.08	1.53	5.10

Table 6.8: Results of Prediction for New Year's Day

Using data	Errors of Prediction (%)					
	1984			1985		
	R.M.S.	M.A.P.	Max.	R.M.S.	M.A.P.	Max.
1983	2.44	1.90	7.24			
1984				3.79	3.22	8.00
1983 & 1984				3.20	2.75	6.78

By using the correction factors, the holiday load could be predicted on the basis of the loads of the same holiday in previous years. Tables 6.6 to 6.8 listed the performance results for these holidays in 1983 and 1984. Figures 6.11 to 6.13 represented the comparison of predicting load with the actual load for Christmas Day, Boxing Day and New Year's Day respectively.

The prediction results in the above three tables are really remarkable with R.M.S. errors being all within 4%. It is generally held that the load

TITLE: Load Prediction for Special Holidays

FIGURE: Prediction for Christmas Day (1984)

— Prediction

- - - Act

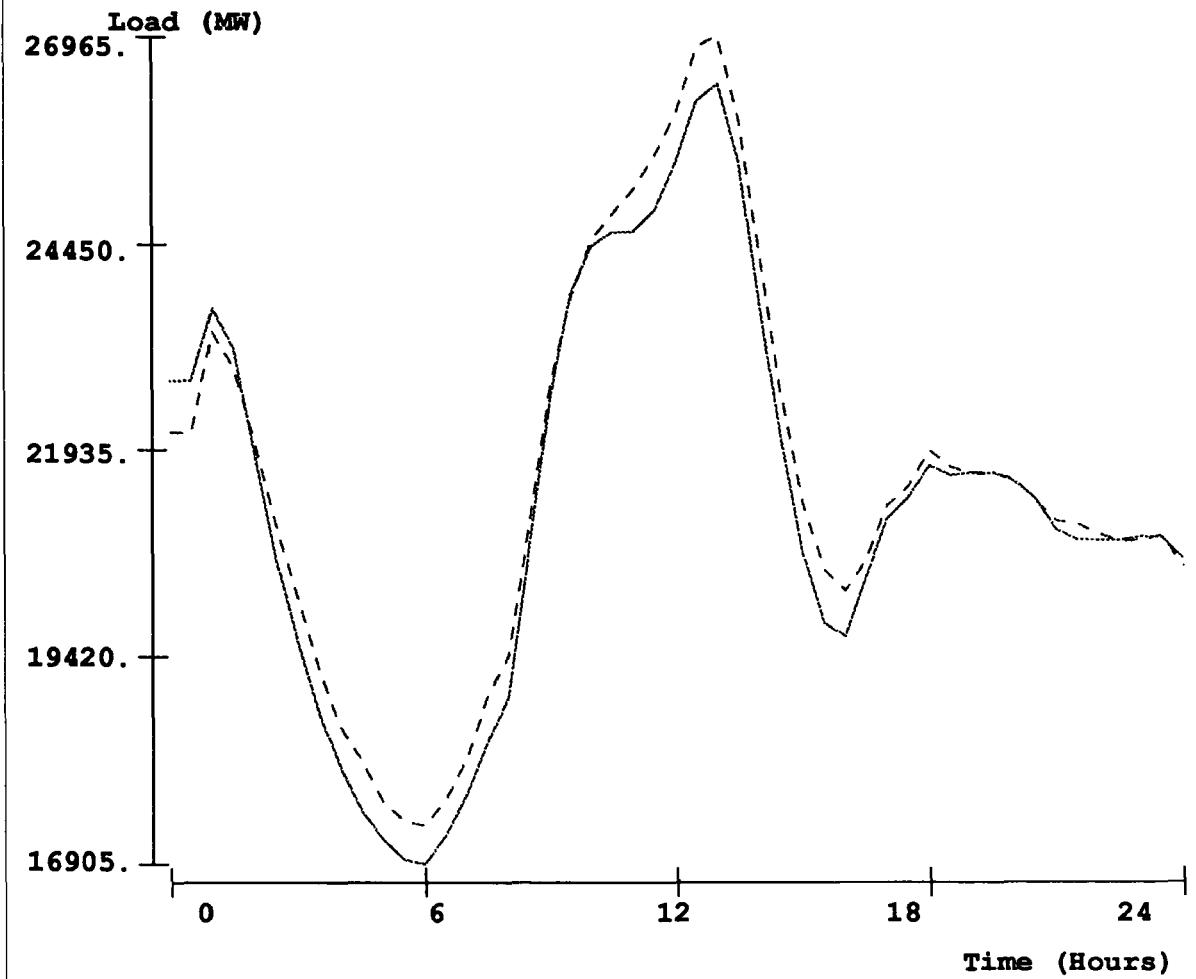


Figure 6.12 Prediction of Loads for Christmas Day

TITLE: Load Prediction for Special Holidays

FIGURE: Prediction for Boxing Day (1984)

— Prediction

- - - - Act

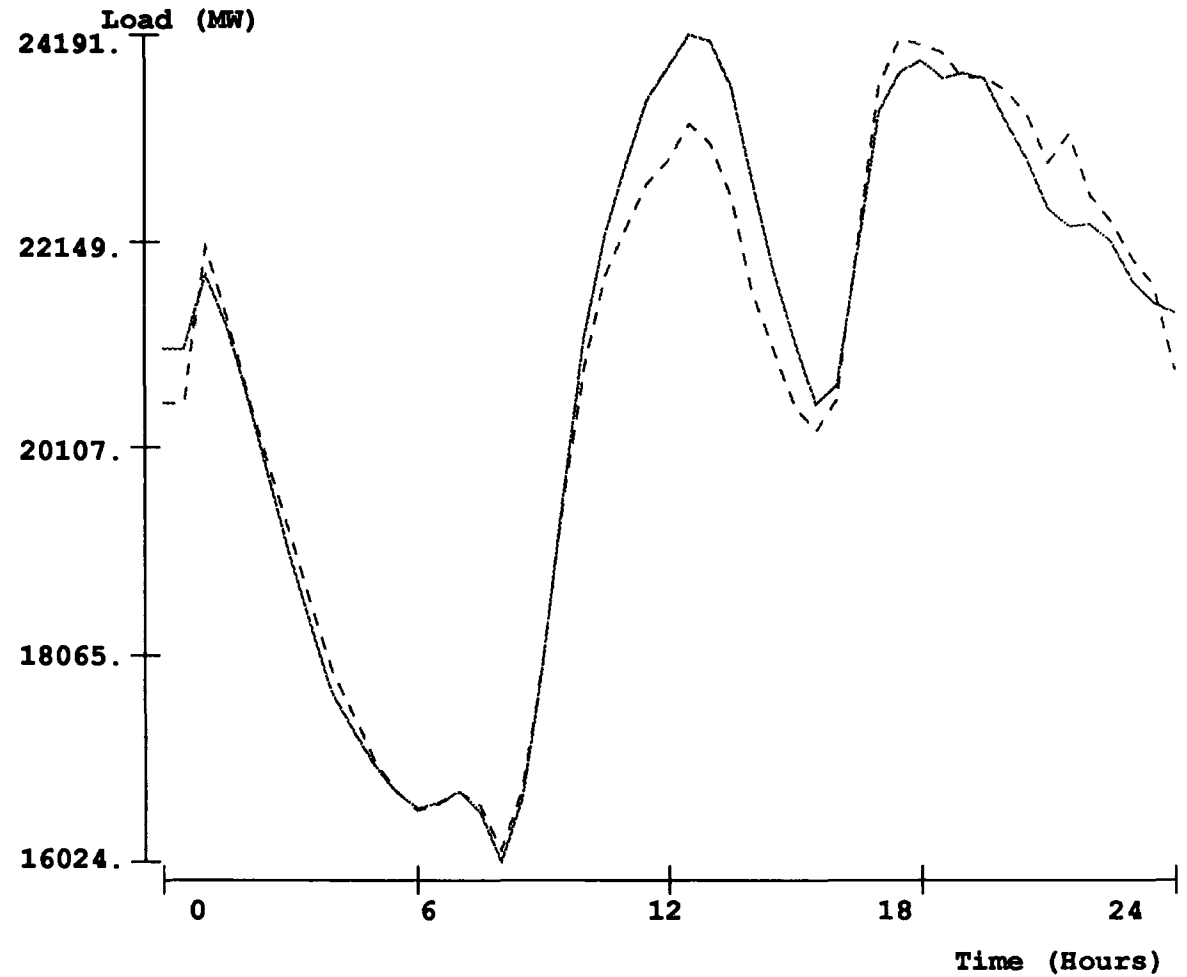


Figure 6.13 Prediction of Loads for Boxing Day

TITLE: Load Prediction for Special Holidays

FIGURE: Prediction for New Year's Day (1985)

— Prediction

- - - - Act

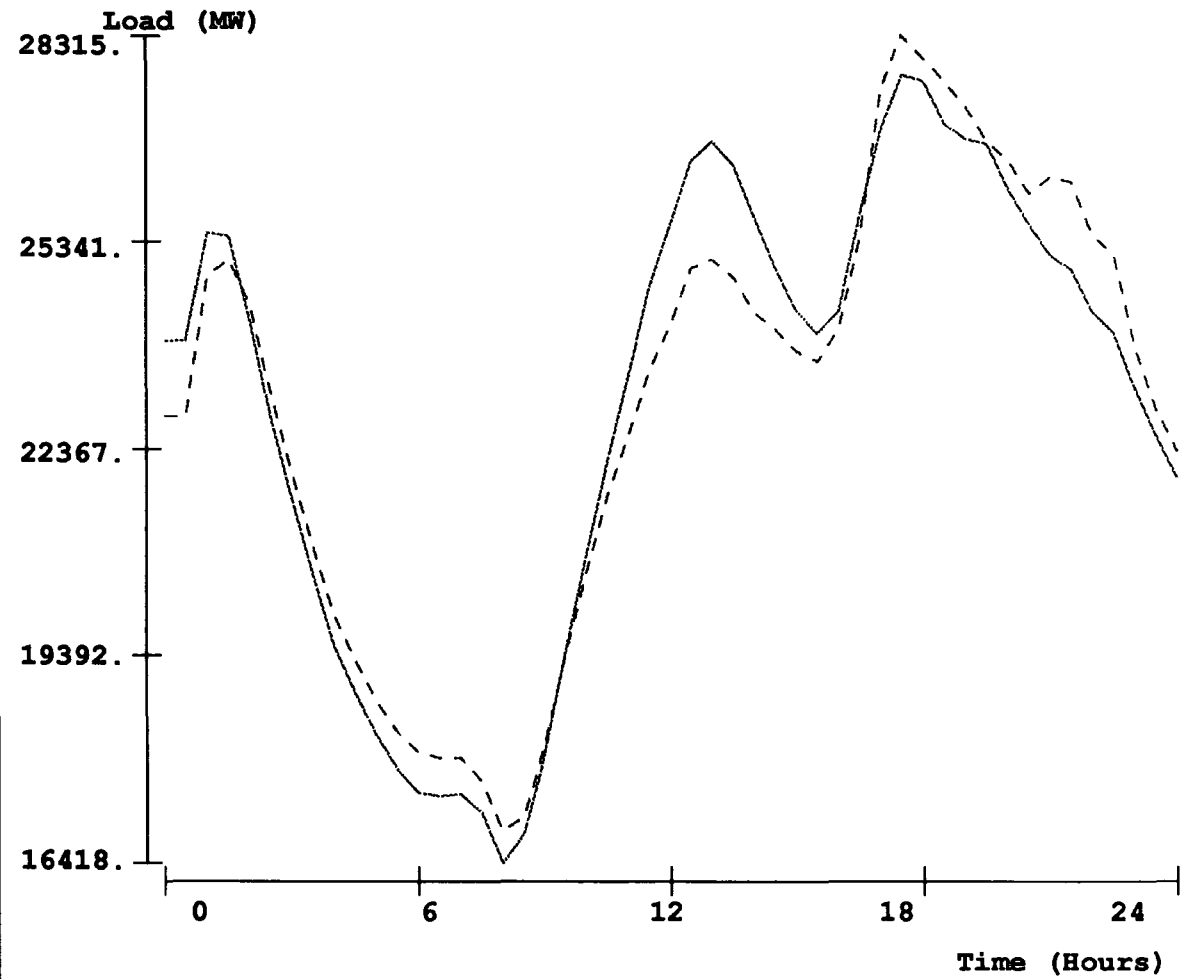


Figure 6.14 Prediction of Loads for New Year's Day

prediction over the period from Christmas day to New Year's day is the most difficult, because some people still have their days off on holiday even though on weekdays. The overall load of weekdays during this period is about 50% - 80% of the normal working-day load only. The load of this period shows a mixture of weekday load with weekend load, with a considerable variation from one day to another.

6.6 Predicting loads over periods between Christmas day and New Year's day

During the periods between Christmas day and New Year's day (and the following two or three days), the actual loads on weekdays are a mixture of holiday loads and weekday loads. The reason is many people have their days off on holiday while some people have to keep on working in order to keep some industrial machinery and commercial activities running continuously. But the electrical demand seems to change from year to year indicated by the variation of load during the same period. It can be simply considered that more load consumed on Christmas day will result in more load being used on the following weekdays, simply because the people working on Christmas day have to work through the whole week. So, to predict the load of a day-of-week within this period, the similar load of the same day-of-week in the same period last year (or previous years) has to be used as a reference load. The correction factors for Christmas Day are used to modify the loads of reference day.

Testing has been made for this period of two years and the results are shown in Tables 6.9 and 6.10. Figures 6.15 and 6.16 show two examples of the prediction results.

Although weather conditions have a very strong effect on the holiday period loads, the situations can be different from that taken in 6.4.2 in that the load/temperature rate is difficult to determine. The weather-sensitive part can not be predicted precisely because there are too many uncertainties for it: the weighting factors of commercial, and domestic loads in the overall load;

TITLE: Load Prediction for Special Periods

FIGURE: Prediction for 27/12/1983 (Tuesday)

— Prediction

- - - - Act

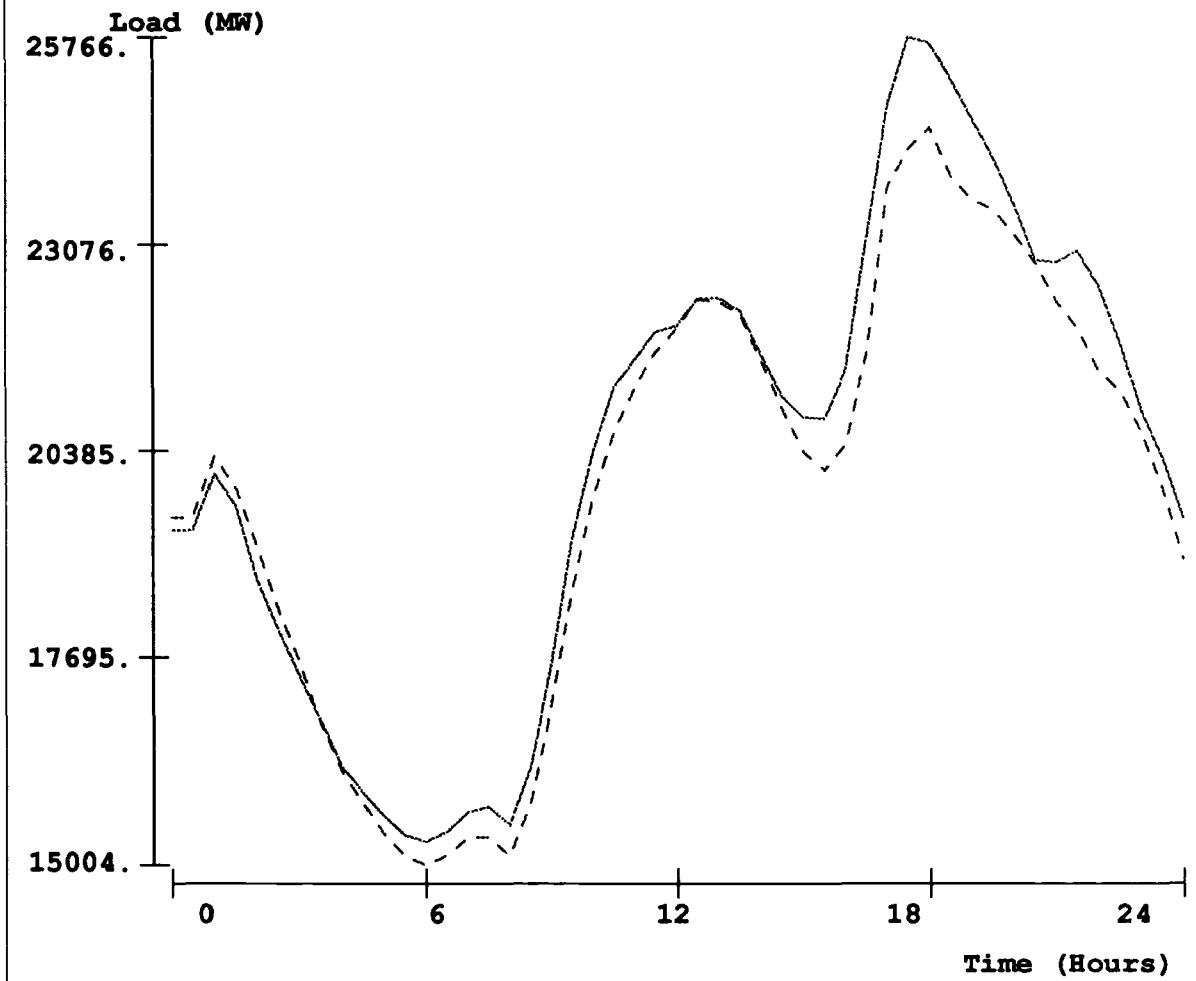


Figure 6.15 Prediction of Loads for 27/12/1983 (Tuesday)

TITLE: Load Prediction for Special Periods

FIGURE: Prediction for 30/12/1984 (Sunday)

— Prediction

- - - Act

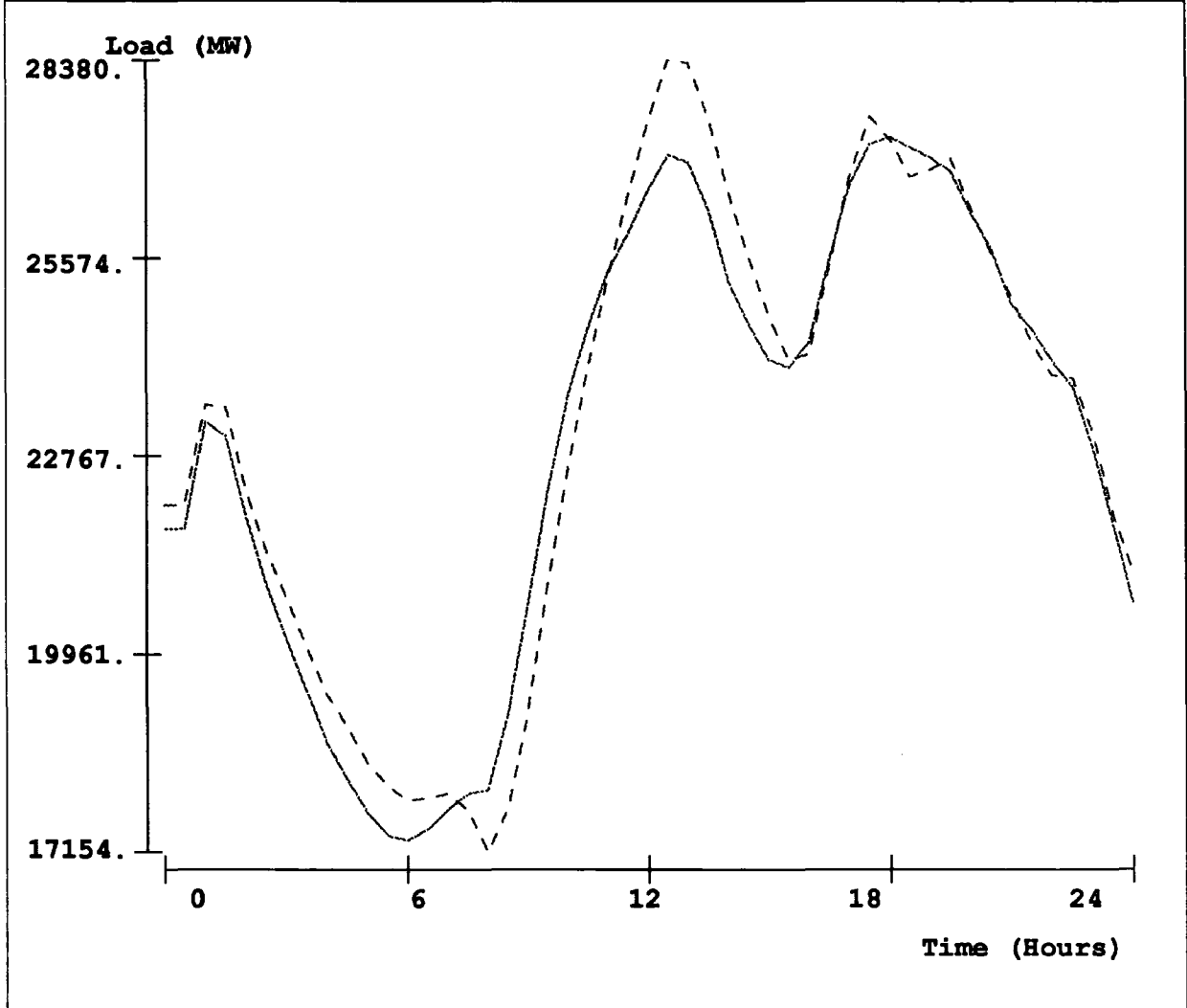


Figure 6.16 Prediction of Loads for 30/12/1984 (Sunday)

weather-sensitive loads inside each load category; response of the consumers towards the change of weather conditions.

Table 6.9: Results of Predicting Load for Periods Between Christmas Day and New Year's Day (1983)

Date	Day-of-week	Reference-day	Error (%)	
			R.M.S.	MAX.
27/12/1983	Tuesday	28/12/1982	2.87	7.00
28/12/1983	Wednesday	29/12/1982	3.77	6.20
29/12/1983	Thursday	30/12/1982	1.16	-2.68
30/12/1983	Friday	31/12/1982	4.92	-14.00
31/12/1983	Saturday	24/12/1983	2.56	6.50

Table 6.10: Results of Predicting Load for Periods Between Christmas Day and New Year's Day (1984)

Date	Day-of-week	Reference-day	Error (%)	
			R.M.S.	MAX.
27/12/1984	Thursday	29/12/1983	2.67	5.60
28/12/1984	Friday	30/12/1983	3.55	-6.50
29/12/1984	Saturday	31/12/1983	2.80	5.49
30/12/1984	Sunday	23/12/1984	3.10	7.90
31/12/1984	Monday	24/12/1984	4.29	-7.14

6.7 Eliminating holiday effects on normal period prediction

The holiday effect is not limited to the holiday itself, but also to the neighbouring days. The property of the holiday effects on neighbouring days

is greatly dependent on the model used: if the model of time series method is ARIMA with hourly and daily cycles only, then the prediction for the next two or three days following the holiday will be affected by the holiday loads. However, if the ARIMA model has a weekly cycle included as well, only prediction for the same day-of-week in the next week is affected. This is shown in Table 6.11 by testing the results of prediction of neighbouring days and weeks following the Spring Bank Holiday of 1983, and Summer Bank Holiday of 1984. From the table, it can be argued that the actual demand data for the periods of holidays cannot be employed by the predictors (ARIMA) for modelling, otherwise, disappointing results might be obtained. Figure 6.18 depicts the accumulative results of R.M.S. errors against lead time over one week using the actual load data by ARIMA with weekly cycle.

Figure 6.18 shows the behaviour of the ARIMA model (including daily and weekly cycles) in predicting the load around the holiday period. Curve II presents the root-mean-squared error (in per cent) against lead time, for predicting loads from Tuesday until the Sunday in the holiday week. It shows that the Monday holiday load does not affect the load for the following days. Curve I in Figure 6.18 is the root-mean-squared error for predicting the whole week (from Tuesday until the next Monday) against the lead time. By comparison, we can see that the holiday effect, using the ARIMA model mentioned, was for the next normal Monday only, but not for the weekdays and weekends.

So, the actual data recorded on the holiday must be avoided or replaced for further prediction. Some modification about the data must be done in order that the ARIMA model can be used further. It is processed in this way:

For the weekdays and weekend (from Tuesday till Sunday), the actual load and the ARIMA model may be directly used for prediction. When predicting the load for the next Monday, the actual holiday loads have to be replaced by moving the actual Tuesday load to the holiday Monday and inserting a normal Tuesday load (the earlier Tuesday) as the load of this Tuesday. This is because the actual load data on that Tuesday which follows the holiday have the similar

TITLE: Effects of Holiday Load on

FIGURE: Neighbouring Days and Weeks

— SP83.RMS ····· SU84.RMS
- - - SP83.MAX ····· SU84.MAX

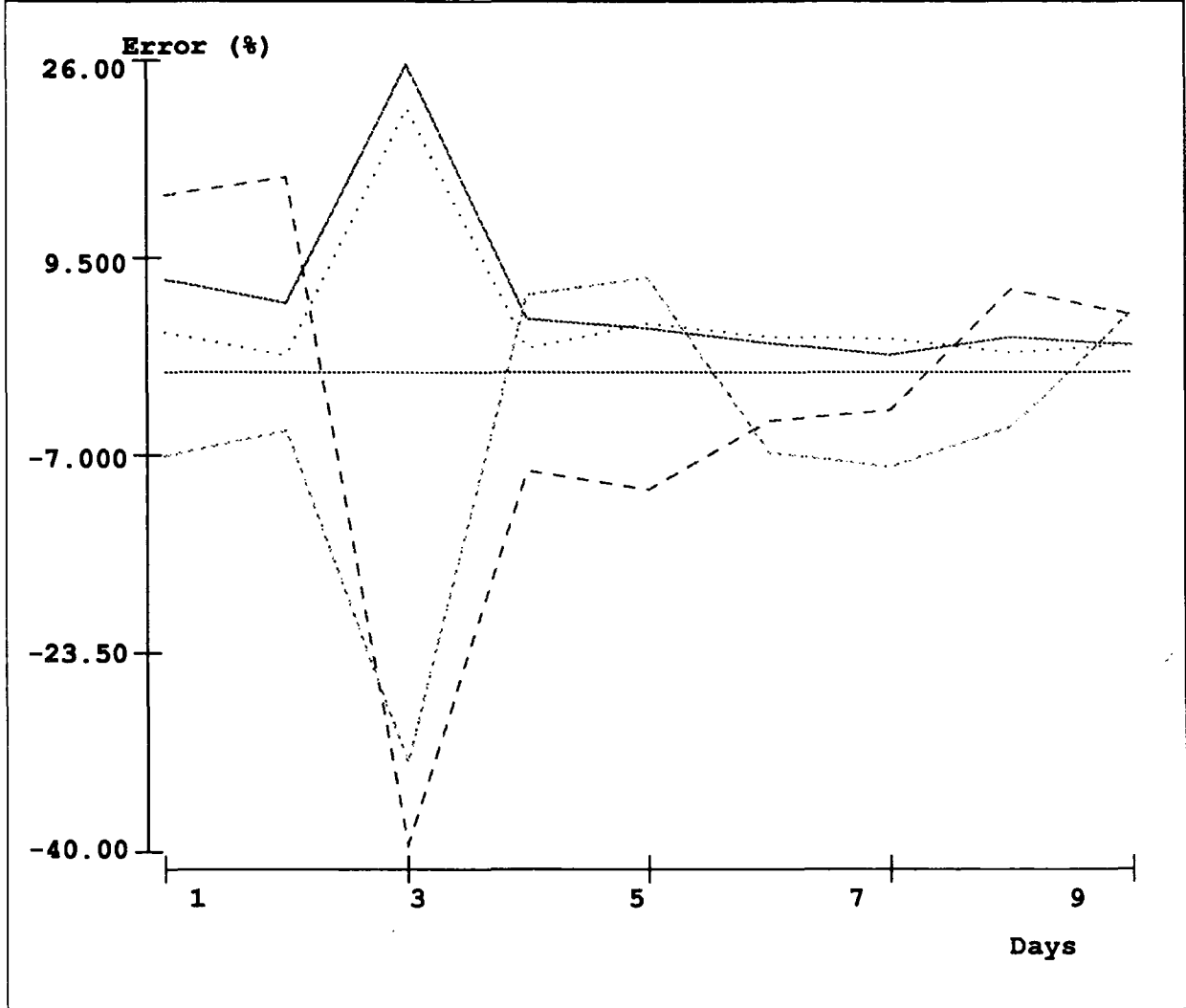


Figure 6.17 Effects of Holidays on Neighbouring Days and Weeks

TITLE: Holiday Effect (1984 Summer Bank Holiday)

FIGURE: Holiday Period Load Prediction by ARIMA

——— HOL84.P;

----- HOL84W.P;

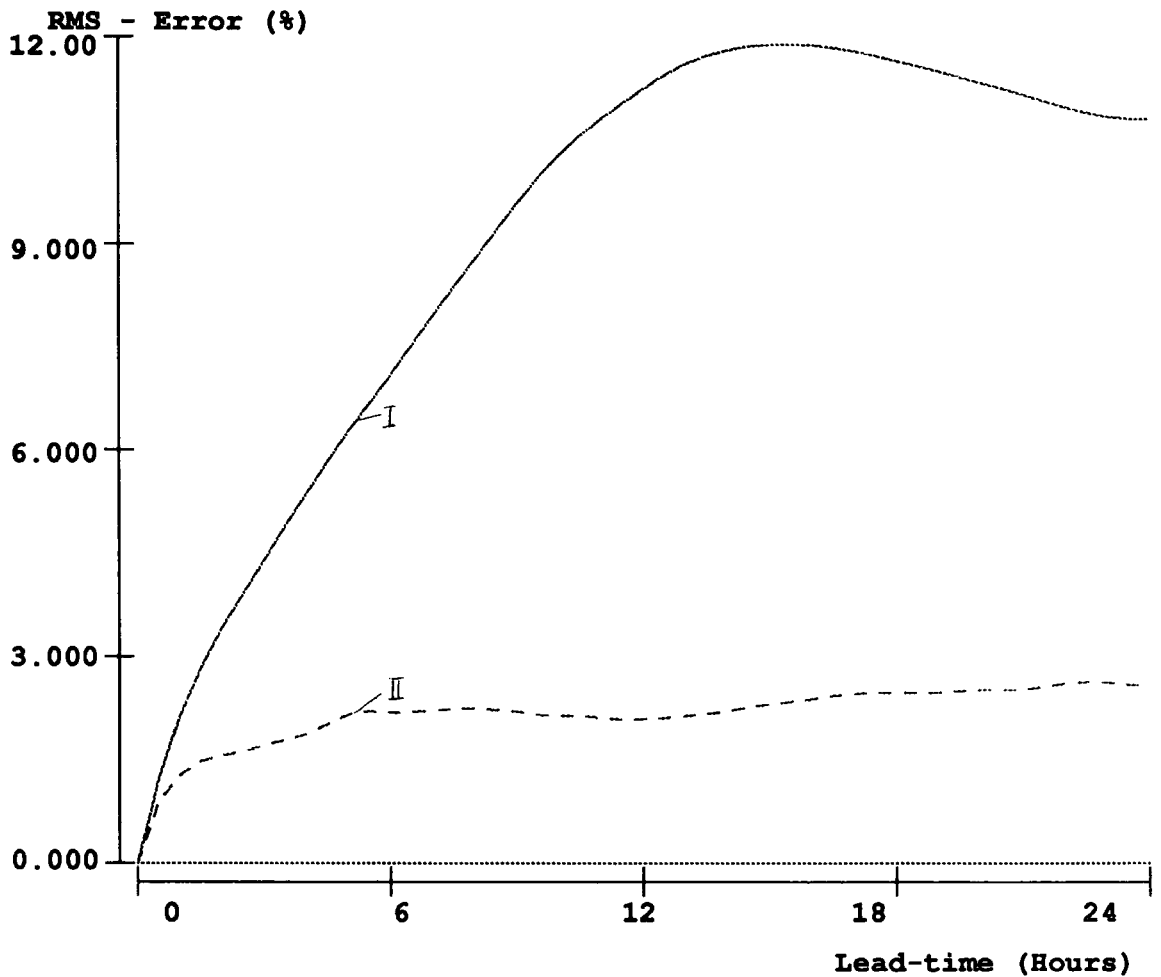


Figure 6.18 Predicting the Holiday Period Load by ARIMA

TITLE: Effect Holiday (1984 Summer Bank Holiday)

FIGURE: Comparison: Pure ARIMA & ES

——— HOL84.P

- - - - HOL84R.P

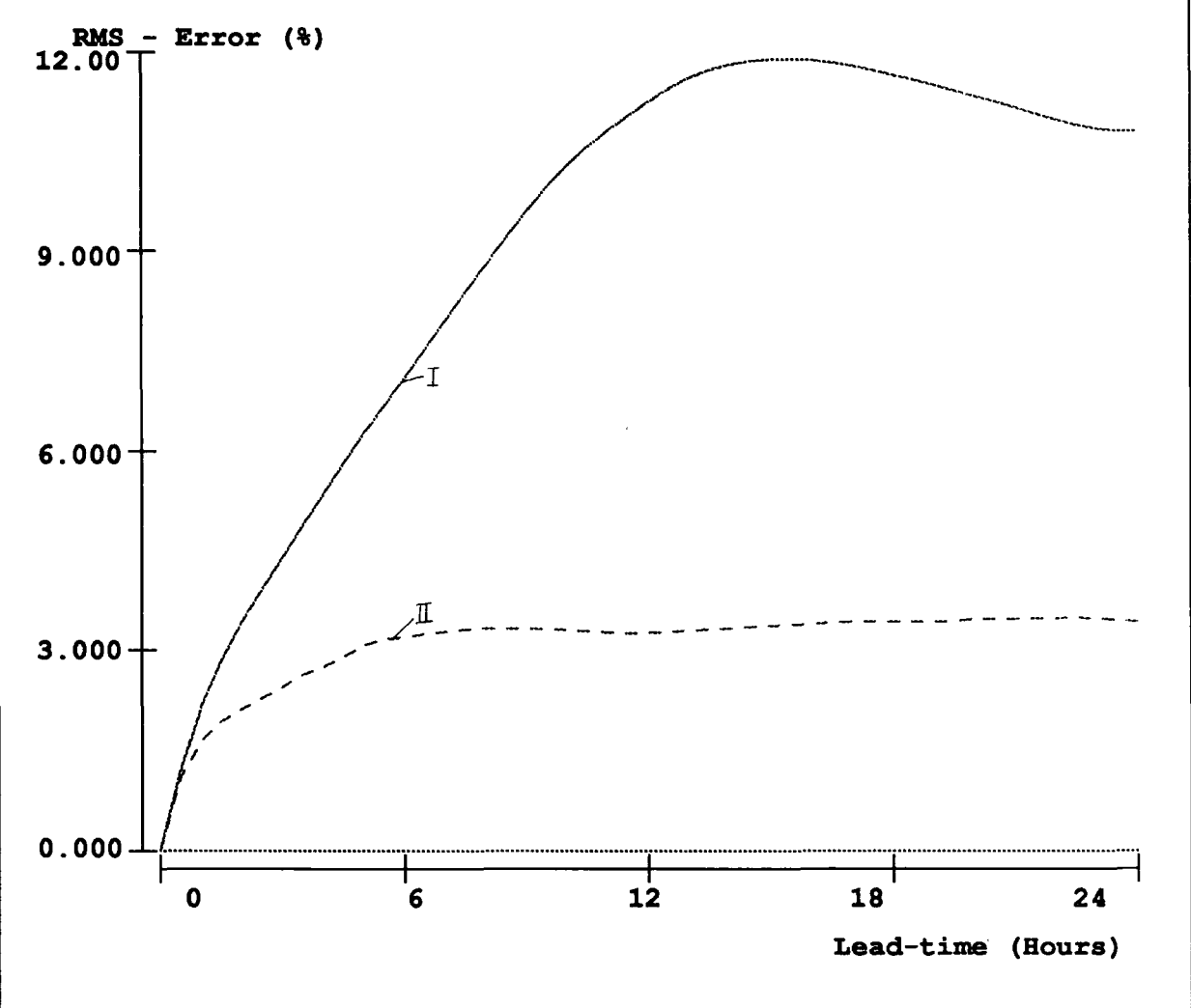


Figure 6.19 Comparison of Two Approaches

pattern as that of normal Mondays: very low at the start of the day and then back to normal load on a working day. So, the actual loads of Tuesday can be used as the Monday load. And the normal Tuesday loads are then inserted for this Tuesday. In this way, the effects of the holiday on prediction will be diminished.

**Table 6.11 Effects of Holidays of ARIMA Method
on Neighbouring Days and Weeks**

	Date	Error(%)		Date	Error(%)	
		R.M.S.	Max.		R.M.S.	Max.
Holiday	30/5/1983			27/8/1984		
	31/5/1983	7.68	14.71	28/8/1984	3.31	-7.08
	1/6/1983	5.74	16.24	29/8/1984	1.40	-4.91
1st week	6/6/1983	25.61	-39.38	3/9/1984	21.98	-32.53
	7/6/1983	4.44	-8.27	4/9/1984	2.01	6.42
	8/6/1983	3.62	-9.87	5/9/1984	4.04	7.83
2nd week	13/6/1983	2.42	-4.12	10/9/1984	2.93	-6.78
	14/6/1983	1.43	-3.24	11/9/1984	2.79	-7.98
3rd week	20/6/1983	2.91	6.84	17/9/1984	1.62	-4.62
	21/6/1983	2.26	4.76	18/9/1984	2.29	5.10

With this implementation, the overall performance of prediction for a whole week was shown in Figure 6.19 (see curve II) compared with that using the actual loads only. This was much improved over the prediction without any modification (see curve I).

6.8 Knowledge about special events

Listed below is some knowledge about the dates of special events, which is stored in the knowledge base:

```
[active holidays public_holidays [summer_bank_holiday 30 8 1982]];
[active holidays public_holidays [christmas_day 25 12 1982]];
[active holidays public_holidays [boxing_day 26 12 1982]];
[active holidays public_holidays [public_holiday 27 12 1982]];
[active holidays public_holidays [new_years_day 1 1 1983]];
[active holidays public_holidays [good_friday 1 4 1983]];
[active holidays public_holidays [easter_monday 4 4 1983]];
[active holidays public_holidays [may_day_holiday 2 5 1983]];
[active holidays public_holidays [spring_bank_holiday 30 5 1983]];
[active holidays public_holidays [summer_bank_holiday 29 8 1983]];
[active holidays public_holidays [christmas_day 25 12 1983]];
[active holidays public_holidays [boxing_day 26 12 1983]];
[active holidays public_holidays [new_years_day 1 1 1984]];
[active holidays public_holidays [good_friday 20 4 1984]];
[active holidays public_holidays [easter_monday 23 4 1984]];
[active holidays public_holidays [may_day_holiday 7 5 1984]];
[active holidays public_holidays [spring_bank_holiday 28 5 1984]];
[active holidays public_holidays [summer_bank_holiday 27 8 1984]];
[active holidays public_holidays [christmas_day 25 12 1984]];
[active holidays public_holidays [boxing_day 26 12 1984]];
[active holidays public_holidays [new_years_day 1 1 1985]];
[active holidays public_holidays [good_friday 5 4 1985]];
[active holidays public_holidays [easter_monday 8 4 1985]];
[active holidays public_holidays [may_day_holiday 6 5 1985]];
[active holidays public_holidays [spring_bank_holiday 27 5 1985]];
[active holidays public_holidays [summer_bank_holiday 26 8 1985]];
[active holidays public_holidays [christmas_day 25 12 1985]];
[active holidays public_holidays [boxing_day 26 12 1985]];
[active holidays public_holidays [new_years_day 1 1 1986]];
```

```
[active days gmt_bst [29 3 1987]];
[active days gmt_bst [30 3 1986]];
[active days bst_gmt [26 10 1986]];
[active days gmt_bst [31 3 1985]];
[active days bst_gmt [27 10 1985]];
[active days gmt_bst [25 3 1984]];
[active days bst_gmt [28 10 1984]];
[active days gmt_bst [27 3 1983]];
[active days bst_gmt [23 10 1983]];
[active days bst_gmt [24 10 1982]];
[active christmas_day factor [saturday 1.05 sunday 1.10]];
[active boxing_day factor [saturday 1.10 sunday 1.10 monday 1.10]];
[active new_years_day factor [saturday 1.10 sunday 1.10]];
```

By storing these facts in the knowledge base, it is easy to find the day-type and the same type of day in previous years. For example, date of 30 August, 1982 is a summer bank holiday (public holiday), so is 29 August, 1983. And date 30 March, 1986 is the day when the time changes from GMT to BST while it changes from BST to GMT on 26 October, 1986.

The last three lines store the correction factors for Christmans Day, Boxing Day and New Year's Day respectively depending on what days-of-week they are.

6.9 Examples of programmes in POP-11

The following two procedures show how the expert systems work in POP-11.

Procedure I is used to find out what the day type is, a normal day-of-week, or a public holiday.

```

define find_public_day_type(day) → special_day;

vars day,special_day,d1,m1,y1,day_in,type,day_s,temp_day-up,temp_day-down;

vars week_day,week_th,day_week;

;;; variable declaration.

if length(day) < 5 then

    day → day_in;

    find_day(day) → week_day;

    weekth_check(day) → week_th;

    [ ^day ^week_th ^week_day ] → day;

endif;

day(1) → d1; day(2) → m1; day(3) → y1;

[ ^d1 ^m1 ^y1 ] → day_in;

;;; to store date in variable day_in.

[ ] → special_day;

foreach [active holidays public_holidays [?type ??day_s]] do

    if day_in=day_s then

        [ ^type holiday ] → special_day;

    endif;

endforeach;

;;; search through the knowledge base if some holiday

;;; has got the same date as day_in.

```

```

if special_day=[ ] then

  foreach [active holidays public_holidays [?type ??day_s]] do

    day_ndays_follow(day_s,1) → temp_day_up;

    day_ndays_follow(day_s,-1) → temp_day_down;

    if day=temp_day_up then

      [^type run-up] → special_day;

    elseif day=temp_day_down then

      [^^type run-down] → special_day;

    endif;

  endforeach;

  ;;; try to find whether day_in is a day before (or after) a holiday

  ;;; if the day_in is not a holiday.

  if special_day=[ ] then

    find_day(day) → day_week;

    [normal_day ^day_week] → special_day;

  endif;

endif;

enddefine;

```

So, the first element in special_day in the output of the procedure indicates the day-type: a holiday, a run-up (or run-down) day or a normal day.

Procedure II illustrates how to pick up the corrective factors for Christmas Day, Boxing Day, and New Year's Day if present day is one of such holidays.

```
define type_factor(special_day,hol_date,hol_ref) → f;

    ;; to pick up the correction factor for reference day.

    1.0 → f_x;

    ;; assign initial value for reference day.

    if member(hd(rev(hol_ref)),[saturday sunday monday]) then

        if present ([active %special_day(1)% factor [== %hd(rev(hol_ref))%

            ?f_x ==]]) then

            ;; doing nothing but pick up f_x.

            endif;

        endif;

    ;; for present day.

    1.0 → f_n;

    if member(hd(rev(hol_date)),[saturday sunday monday]) then

        if present ([active %special_day(1)% factor [== %hd(rev(dat_r))%

            ?f_n ==]]) then

            ;; doing nothing but pick up f_n.

            endif;

        endif;

    realof(f_x/f_n) → f;

enddefine;
```

6.10 Discussion and conclusion

National holidays have a special influence on short-term load prediction, which often presents problems in producing satisfactory and accurate prediction. This chapter has been devoted to the discussion of how to solve these problems, through the analysis of the characteristics of holiday loads and treating their features individually in the actual prediction process.

Because the short period of load prediction lacks repetition of holidays which is of most concern in the procedure, the conventional time series methods prove to be unable to deal with the prediction of holiday loads. It is suggested in the chapter that they can be forecast separately from the neighbouring days by using different approaches. A new approach has been thus formed in the chapter to complete the task. This new approach uses the weekend load preceding the holiday as reference instead of relative gaps.

Weather conditions also have a great influence on holiday loads as they do on normal loads. No load prediction can be ideal without considering the effects of weather conditions upon loads. This approach possesses the advantage of having the weather factors included in prediction process if these weather factors are adjusted in advance. However, other approaches neglect this and therefore can not fulfil the prediction of holiday loads.

Predicting the loads of some special periods can also be meaningful, such as that of Christmas Day and New Year's Day. The author introduced for the first time the ways of estimating those loads. Having tested the method, the author found it feasible to produce good prediction results for those special periods by factoring the loads of same periods in past years depending on what days-of-week these holidays are.

Another important finding in this study is that if more historical holiday data are available for use, better prediction results can be obtained for holiday load prediction.

Actual holiday load data must be altered or replaced in order that they will not influence the conventional time series method to predict loads for the neighbouring days. A simple replacement of the actual holiday loads by normal loads only, can diminish the holiday effects on neighbouring days when the ARIMA method of weekly cycle is used.

The approaches for different holidays proposed in this chapter are simple and easy to use. The main computational time is spent on pattern matching for finding the appropriate load data in the past which are stored in the database. The employment of POP-11 makes it very efficient.

CHAPTER 7

LOAD FORECASTING INCLUDING WEATHER EFFECTS

7.1 Introduction

Box-Jenkins time series methodology has been applied [2, 18, 65, 85, 94, 126, 163, 191, 208, 234, 256] to short-term load forecasting, and shown to perform well in most cases. In short, the Box-Jenkins methodology is an iterative procedure by which a model is constructed. The process proceeds from the most simple structure, with the least number of parameters, to as complex a structure as is required to obtain an 'adequate' model - 'adequate' in the sense of yielding white residuals. Four steps are involved in building the model and performing prediction. The first step is an identification of structure (model) and employs sample autocorrelation patterns. After a structure has been chosen the next step involves an estimation of the coefficients inherent in the structure description. Next the optimal parameter estimates are inserted into the model to generate its estimated residuals. These are then subjected to diagnostic procedures to determine if they are indeed 'white'. If not, their sample autocorrelation function is used to hypothesise a new structure and the cycle is begun anew. If the model satisfies all diagnostic tests it may then be implemented for on-line testing. The benefits of such a methodology are many, but primarily one will always be assured of a model which has the fewest possible parameters while still explaining all the systematic variation in the random errors. As a whole, the method is to generate a model from the record of past load itself, to perform prediction on a series of 'white' noise.

However, it has been realised [23, 54, 64, 92, 97, 132, 136, 182] that, in order to obtain an accurate prediction of future load, weather effect on electrical demand should not be neglected. Usually the overall load can be categorised

as non-weather- and weather-sensitive components. The seasonal cycle in the load is indirectly taken into account by the ARIMA model, because it takes more weighting on the recent data in the updating of the parameter estimates of the weather insensitive component. But when the weather conditions change abruptly, the weather-sensitive component has to be estimated separately.

The most influential factors of weather conditions are temperature, wind speed, humidity and cloud cover, because they directly affect the heating load and lighting load. If weather information is used properly, the accuracy of load prediction can be improved. Some applications [32, 92, 127, 162, 182] introduce linear or non-linear transfer functions of temperature into the ARIMA model to provide multivariate predictor. Although some authors [18, 94, 162] presented better results by the introduction of such transfer functions, most do not favour it, because the model will become much more complicated, and need regular weather input. Otherwise, the model will be interrupted.

Although it is proposed in chapter 4 that the overall load can be disaggregated into its components such as domestic heating load, commercial lighting load, on which weather effects can be easily taken into account, the disaggregated components can not be directly used in this chapter due to absence of proper data to validate the results. In order to simplify the load prediction procedure, the weather effect on loads is considered only for weekends. This is because the weather-sensitive loads make only a small contribution of the overall load during the weekdays. However, on the weekends, domestic loads are the dominant part of the overall load, and the weather-sensitive loads occupy a large amount of domestic load. Moreover, the developed ARIMA model can predict weekday loads with a satisfactory accuracy [79]. Consequently, weather conditions are used to be included in the model only for predicting the load for weekends.

This chapter emphasises how load forecasting can be improved for weekends by taking the weather effect into consideration within an ARIMA model, rather than using a transfer function of temperatures. Due to limited available weather information, only the maximum temperature of a day is used as the

effective variable. The chapter is arranged as follows: section 7.2 discusses weather variables which have to be included in the prediction. Then follows the description of the data used for prediction including load and weather information. Section 7.4 presents the interface between FORTRAN 77 and POP-11. The next three sections will be devoted to the presentation and discussion of three modifications: in section 7.5, simple averaging of predicted load with the actual load is used for further prediction; section 7.6 takes into consideration quantitatively the weather information; then, in section 7.7, real weather information is used to adjust the historical load data for prediction. A discussion and conclusion is drawn in section 7.8.

7.2 Weather variables to be included in the models

The relationship between the weather variables and electrical demand has to be found in order to predict further load on the condition that further weather conditions have been forecast for the predicted period of time.

Some models [54, 97, 123, 131, 197, 224] have included many weather variables such as the maximum temperature, minimum temperature, wind speed, illumination, humidity, cloud cover by regression studies. Since these weather variables are provided by the Meteorological Office, there are sometimes errors in prediction. Use of such imprecise weather information could cause more load prediction errors compared with the univariate models. In addition, such multi-variate models need regular weather variable inputs when they are used for on-line prediction. Some models use selected weather variables, for example, the average daily temperature and the average wind velocity only. Because the relationship between the weather variables and the load is non-linear, some applications [92, 116, 127] use non-linear transformation of the temperature variable to formulate a linear weather-load model. One of the many possible transformations is of the form:

$$WV(i) = \begin{cases} TMP(i) - T_s & \text{if } TMP(i) > T_s \\ 0 & \text{if } T_w < TMP(i) < T_s \\ T_w - TMP(i) & \text{if } TMP(i) < T_w \end{cases}$$

where T_w and T_s are the fixed parameters of the transformation and $TMP(i)$ is the average temperature on the i th day. This implies that the model is linear when the temperatures are higher (or lower) than the fixed parameters. Using this kind of transformation, T_s and T_w have to be chosen carefully.

However, the developed univariate ARIMA model generally performs well, especially when no abrupt changes exist in the past data and present load [79]. In order to make the most use of the advantage, the model is used to predict load for normal weekdays. For weekends, prediction can be improved by taking into account of weather effects. It is evident that the ARIMA model with weekly cycle is not disturbed very much by the weekday loads when it is used to predict loads for weekends. Therefore, only weather information of the weekends (previous and present) need to be added to the model to improve the prediction for the weekends. For example, only the weather data of past Saturdays or Sundays and of the present one are used. As stated earlier, too many weather variables may cause more errors in prediction because of weather forecast errors. Since the temperatures (maximum and minimum within a day) are the most influential factors of the weather information, and most large errors from the ARIMA model occur around the peak load time, the temperature, which causes the load change around peak time, should be modelled. In this case, only maximum temperatures of the weekends are introduced to improve the ARIMA model for weekend load prediction.

7.3 Data for prediction

So far, available data used to test the prediction performance are:

Load data:

Half-hourly recorded load data from the CEGB system, covering the whole area of England and Wales from the year of 1983 to 1985, stamped under the GMT time system. It is found that the loads on weekends have different demand characteristics from on weekdays, especially in the region of peak loads. The loads are found to be identical from one weekend to another.

Loads on weekends also change more frequently, during day-time and evening hours, than on weekdays. The data are reformatted into the form of a list of 48 loads within 24 hours following the calendar date, in which indicators of the nth week of the year and of the day-of-week are included. For example, the following information is in database in order to be accessed for 24/6/1984:

[24 6 1984 26 Sunday]

[14101 13620 13204 12922 12719 12474 12253 11895 11815 11893
12514 13131 14118 15276 16619 17863 18851 19748 20310 21025
21519 22001 22312 22038 20666 19372 18635 18123 17626 17524
17662 18121 18456 18613 18595 18672 18840 18707 18602 18600
19444 20295 20521 19828 18071 16369 15021 13994]

which means 24/6/1984 is the 26th Sunday with the load demand of 48 half-hourly data in the list.

As a result, load levels and date can be easily referred to.

Weather data:

Since detailed weather condition records which cover the same area as corresponding to the load data are not available, the only available weather information is that recorded by Heathrow airport, such as temperatures (both maximum and minimum), wind speed, and sun shine hours within one day. Because no meteorological forecast records are available to be used at each load prediction step, for the period under consideration, the load prediction errors due to incorrect weather forecast are neglected.

The following weather data are stored in database in order to be accessed:

[23 6 1984 25 saturday]

[19.7 0 0 0]

[24 6 1984 26 sunday]

[18.3 0 0 0]

[25 6 1984 26 monday]

```

[22.9 0 0 0]
[26 6 1984 26 tuesday]
[25.8 0 0 0]
[27 6 1984 26 wednesday]
[24.4 0 0 0]
[28 6 1984 26 thursday]
[17.4 0 0 0]
[29 6 1984 26 friday]
[18.8 0 0 0]
[30 6 1984 26 saturday]
[19.4 0 0 0]
[1 7 1984 27 sunday]
[21.9 0 0 0]

```

In the list following the date, the weather data are stored in order of maximum temperature, minimum temperature, sun-rise and sun-set time. The "0" indicates non-data available.

7.4 Interface between FORTRAN and POP-11

The ARIMA model has been written in FORTRAN 77. The knowledge based system is written in POP-11 and all the programmes are run in POPLOG environment which supports POP-11, PROLOG and LISP languages. For the sake of simplicity and saving computation time, the subroutine of the ARIMA model is called directly in POP-11 by the function of "external_load".

The function of 'external_load' is to access external procedures (written in FORTRAN, PASCAL, C) in POP-11. The 'ARIMAHOL' is a subroutine written in FORTRAN 77 to perform ARIMA prediction. The equivalent in POP-11 is named 'arimacall' which accesses the 'ARIMAHOL' by its objective file 'aihol.obj'.

```

external_load('l.arimahol',
              ['aihol.obj'],

```

```

[{type procedure}
[ARIMAHOL arimacall]]);
```

The following procedure is used as a medium to pass variables to and from the programme of ARIMA model. The variable 'lpast' is a vector of electrical demand data of the time series; 'mpast' is the length (number) of historical data while 'mpred' is the lead time of prediction. The three variables are produced in POP-11 procedures. When the three variables are passed to the ARIMA model, the ARIMAHOL is executed and the results are given to 'pred' and 'rmserr' which are the predictions and the R.M.S. error respectively.

```

define pred_call_arima(lpast,mpast,mpred) → pred → rmserr → niter;

  vars lpast,mpast,mpred,pred,rmserr,niter,npast,npred;
  ;;; variable declaration.
  recordclass int32 dummy value:32;
  consint32(0,0) → npast;
  consint32(0,0) → npred;
  consint32(0,0) → niter;

  mpast → value(npast);
  mpred → value(npred);
  vectorclass vfloat decimal;
  initvfloat(mpast) → past;

  for i from 1 to mpast do
    lpast(i) → past(i);
  endfor;

  initvfloat(mpred) → rmserr;
  initvfloat(mpred) → pred;
  ;;; the above is used for data link.
  arimacall(past,npast,npred,rmserr,pred,niter,6,false); ;;; calling ARIMA.
enddefine;
```

The variable 'lpast' is formed in POP-11 by different modifications of recorded historical data which are described in the next sections.

7.5 Prediction by averaging predicted load with actual load

The ARIMA model $((1, 0, 1)_1 \times (1, 0, 1)_{48} \times (0, 1, 1)_{336})$ needs the previous six weeks of data for parameter estimation [79] in order to perform prediction. Since the load reflecting the unusual past weather conditions will affect further predictions, load data of the most recent weekends should be corrected for predicting the load corresponding to the present weather conditions. In other words, if the weather conditions of the past weekends and the present one have the same trend (monotonically increasing or decreasing) in temperature changes, the past load data can be directly used in the model. If not, efforts should be made to modify the abnormal past load data under that particular past weather condition to an artificial one, so that more satisfactory load prediction can possibly be achieved for the current weather conditions. As has been stated earlier, the impact of weather conditions upon loads for weekends is more than on weekdays. Also as it has been seen in chapter six that, the ARIMA model for the CEGB system is sensitive to the loads of the same days-of-week in previous weeks, but not heavily affected by the loads of neighbouring days. So, if the weather conditions of the same days-of-week in previous weeks are not the same, nor of the same trend, then, the load increase or decrease, caused by the weather conditions of the same days-of-week, should be eliminated for further prediction.

The simplest modification is to take the average of the predicted loads and the actual recorded loads of the previous day-of-week as past loads. If the prediction errors for the last weekend are very big, i.e., the predicted loads are far away from the recorded ones, it can be concluded that either the past weather conditions of the earlier weekends were contributors to the errors or the actual weather conditions of the day were special. The weather contribution for either case would be lessened for predicting the current loads if the predicted loads and the actual loads were averaged.

**Table 7.1: Comparison of ARIMA with Load Averaging
for
Winter Saturdays**

Date	Temp. °C	ARIMA(%)		Load-AVG(%)	
		R.M.S.	Max.	R.M.S.	Max.
3/3/1984	8.0	5.34	13.81	3.57	10.35
10/3/1984	8.1	2.22	-5.27	1.11	2.66
17/3/1984	5.8	2.39	-4.01	3.15	-5.73
24/3/1984	7.9	3.53	10.21	2.89	9.41

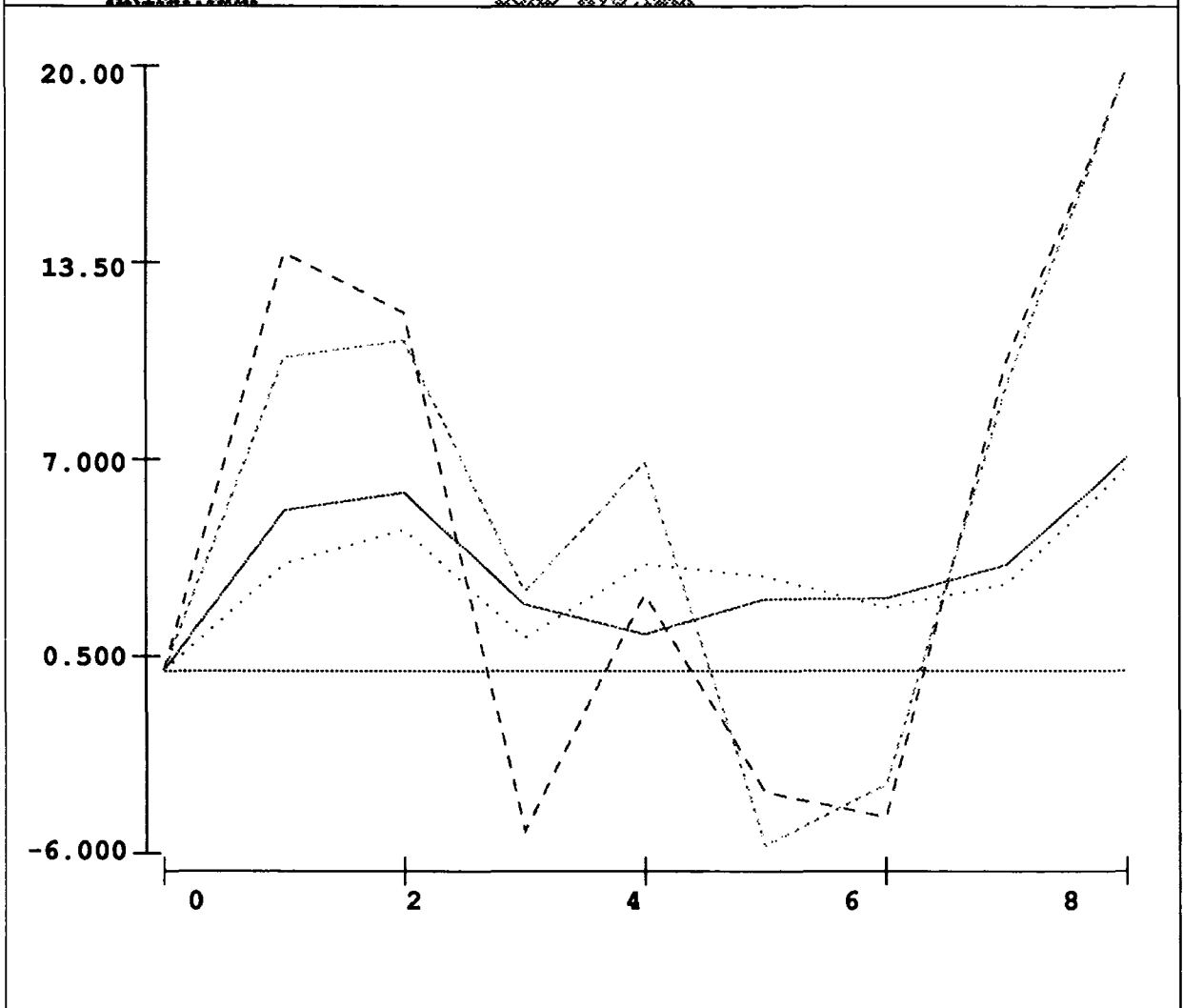
**Table 7.2: Comparison of ARIMA with Load Averaging
for
Winter Sundays**

Date	Temp. °C	ARIMA(%)		Load-AVG(%)	
		R.M.S.	Max.	R.M.S.	Max.
4/3/1984	7.3	5.92	11.82	4.71	10.91
11/3/1984	10.5	1.23	2.56	3.56	6.89
18/3/1984	5.8	2.42	-4.82	2.12	-3.78
25/3/1984	7.8	7.07	19.85	6.75	19.89

TITLE: Comparison of ARIMA with Load Averaging

FIGURE: of Winter Weekends

——— ARIMA.RMS ······ LOAD_AVG.RMS
- - - - ARIMA.MAX ······ LOAD_AVG.MAX



**Figure 7.1 Comparison of ARIMA with Load Averaging
of Winter Weekends**

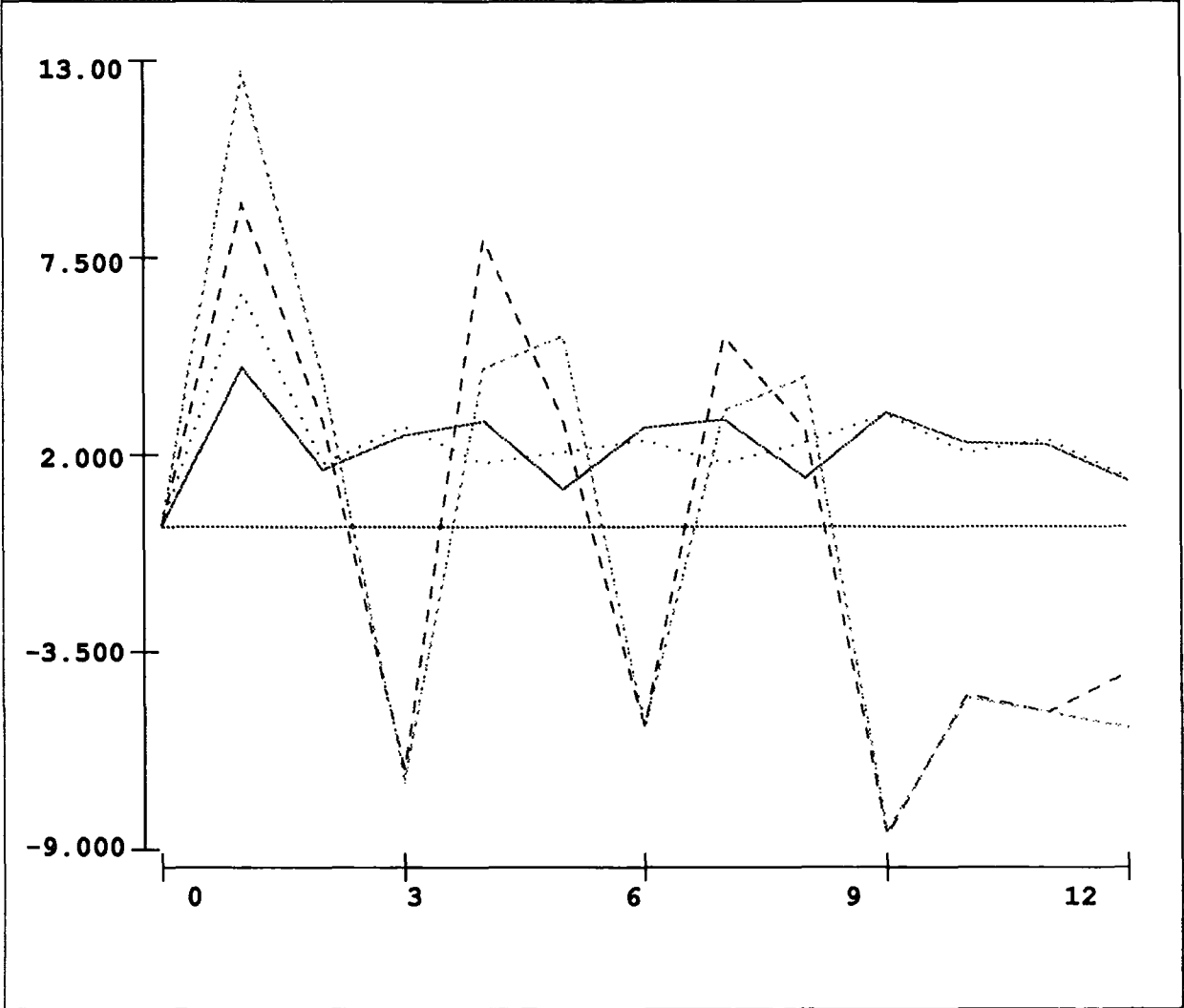
**Table 7.3: Comparison of ARIMA with Load Averaging
for
Summer Saturdays**

Date	Temp. °C	ARIMA(%)		Load-AVG(%)	
		R.M.S.	Max.	R.M.S.	Max.
9/6/1984	23.3	4.43	9.05	6.52	12.62
16/6/1984	23.2	1.59	2.92	1.76	4.16
23/6/1984	19.7	2.53	-6.85	2.78	-7.06
30/6/1984	19.4	2.92	8.05	1.75	4.38
7/7/1984	28.2	1.05	2.91	2.08	5.32
14/7/1984	19.9	2.74	-5.68	2.40	-5.60
21/7/1984	27.3	2.97	5.35	1.77	3.22
28/7/1984	30.6	1.36	2.74	2.35	4.16
4/8/1984	19.8	3.17	-8.63	3.12	-8.50
11/8/1984	23.1	2.33	-4.78	2.06	-4.78
18/8/1984	25.9	2.28	-5.20	2.43	-5.20
25/8/1984	23.7	1.29	-4.13	1.38	-5.63

TITLE: Comparison of ARIMA with Load Averaging

FIGURE: of Summer Saturdays

— ARIMA.RMS ······ LOAD_AVG.RMS
- - - ARIMA.MAX ······ LOAD_AVG.MAX



**Figure 7.2 Comparison of ARIMA with Load Averaging
of Summer Saturdays**

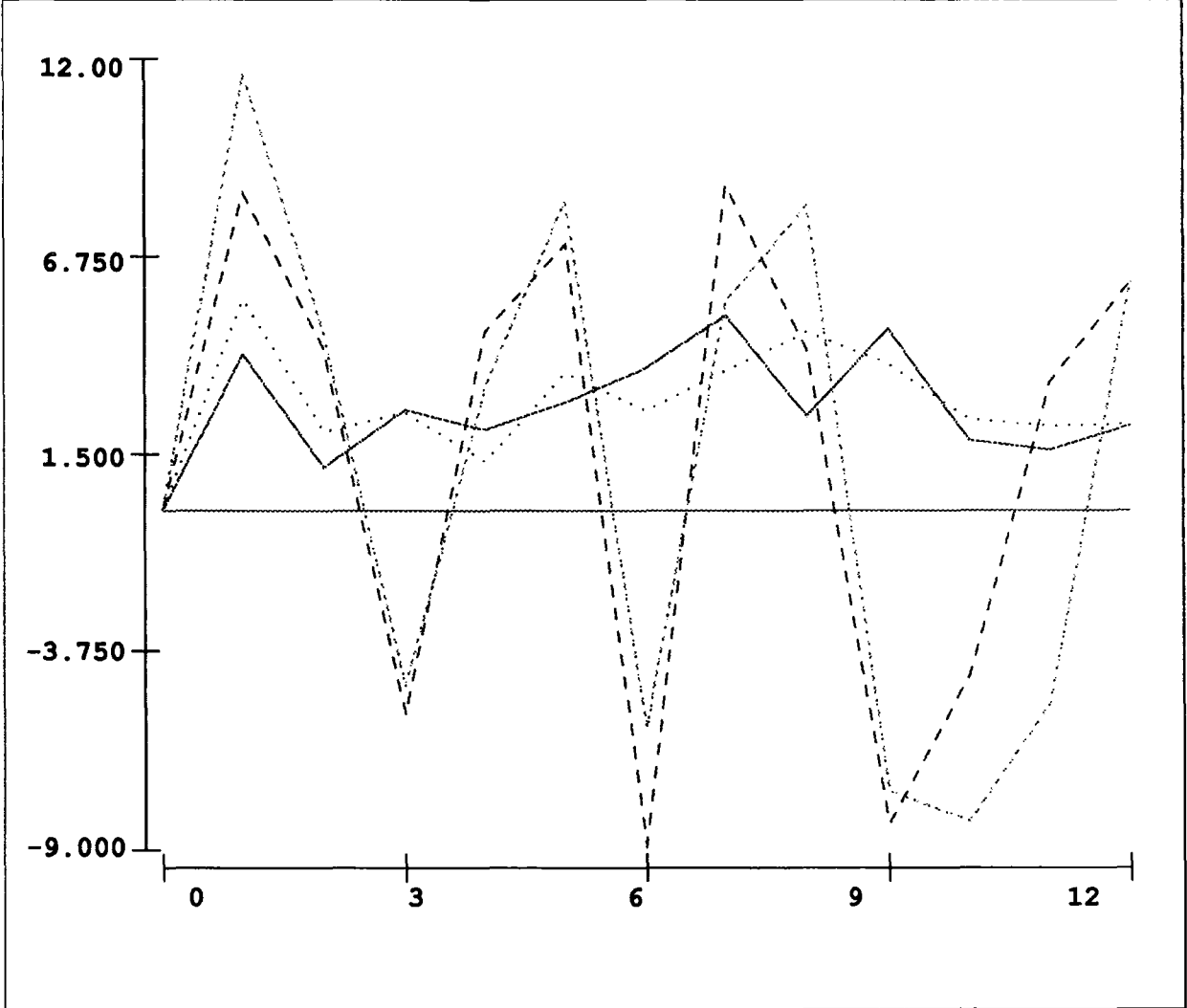
**Table 7.4: Comparison of ARIMA with Load Averaging
for
Summer Sundays**

Date	Temp. °C	ARIMA(%)		Load-AVG(%)	
		R.M.S.	Max.	R.M.S.	Max.
10/6/1984	24.6	4.14	8.43	5.60	11.59
17/6/1984	25.3	1.14	4.29	2.10	4.69
24/6/1984	18.3	2.67	-5.43	2.60	-4.68
1/7/1984	21.9	2.14	4.73	1.30	3.26
8/7/1984	31.7	2.87	7.06	3.64	8.21
15/7/1984	18.9	3.76	-8.86	2.65	-5.78
22/7/1984	25.8	5.16	8.64	3.70	5.55
29/7/1984	28.4	2.50	4.24	4.72	8.09
5/8/1984	19.8	4.81	-8.32	3.89	-7.46
12/8/1984	23.6	1.87	-4.41	2.43	-8.25
19/8/1984	28.8	1.61	3.40	2.24	-5.12
26/8/1984	23.5	2.27	6.07	2.30	6.07

TITLE: Comparison of ARIMA with Load Averaging

FIGURE: of Summer Sundays

— ARIMA.RMS ······ LOAD_AVG.RMS
- - - ARIMA.MAX ······ LOAD_AVG.MAX



**Figure 7.3 Comparison of ARIMA with Load Averaging
of Summer Sundays**

Prediction was tested over two periods (winter and summer) in 1984 by such a simple average. The results by this modification compared with that by the original ARIMA model are listed in Tables 7.1 to 7.4. The tables indicate root mean squared and maximum errors of 48 predictions for the next 24 hours when prediction was made at midnight on that day.

From Tables 7.1 to 7.4, it can be seen that the prediction, simply by averaging the predicted load with the actual load for the previous day-of-week, does not always perform better than the original ARIMA prediction. The reason is simple. Because the averaged loads are based on the assumption that the corresponding weather conditions were normal and the recorded loads disagreed, in most cases, with the general load behaviour. This, nevertheless, might not be always true, as the present weather conditions do not naturally match the ones corresponding to the modified loads, and sometimes have sudden changes. So, it is necessary to determine what kind of load pattern and load level for the past load behaviour approaches closer to the present load under the current weather conditions. To solve the problem, the best way is perhaps to find out the decisive factors from all the contributing ones, although it seems to be very difficult to identify their relationships quantitatively.

7.6 Prediction by error threshold detection

Instead of simple averaging of predicted load with the actual load for previous day-of-week, a further modification has been investigated. An error threshold is used to determine the period of unusual loads occurring in previous weeks in order to eliminate the data noise. If the periods in which the errors were over the preset error threshold last longer than 2 hours, for example, it can be hypothesised that the loads were disturbed by a sudden change of weather conditions. In this case, the loads within such periods are averaged with the predicted ones for the previous day-of-week. If the errors are below the threshold, the actual load data are used directly. As an example, a threshold of 1.5 %, was tested over the same periods as those tested before, and the results are listed in Tables 7.5 to 7.8.

**Table 7.5: Comparison of ARIMA with Error-threshold-detection
for
Winter Saturdays**

Date	Temp. °C	ARIMA(%)		Load-AVG(%)		Error-T-D(%)	
		R.M.S.	Max.	R.M.S.	Max.	R.M.S.	Max.
3/3/1984	8.0	5.34	13.81	3.57	10.35	3.62	10.35
10/3/1984	8.1	2.22	-5.27	1.11	2.66	1.12	2.67
17/10/1984	5.8	2.39	-4.01	3.15	-5.73	3.07	-5.73
24/3/1984	7.9	3.53	10.21	2.89	9.41	2.97	10.16

**Table 7.6: Comparison of ARIMA with Error-threshold-detection
for
Winter Sundays**

Date	Temp. °C	ARIMA(%)		Load-AVG(%)		Error-T-D(%)	
		R.M.S.	Max.	R.M.S.	Max.	R.M.S.	Max.
4/3/1984	7.3	5.92	11.82	4.71	10.91	4.78	11.20
11/3/1984	10.5	1.23	2.56	3.56	6.89	3.57	6.89
18/10/1984	5.8	2.42	-4.82	2.12	-3.78	2.16	-4.00
25/3/1984	7.8	7.07	19.85	6.75	19.89	6.77	19.90

TITLE: Comparison of ARIMA with Error-threshold-detection

FIGURE: of Winter Weekends

— ARIMA .RMS ······ LOAD_AVG .RMS - - - - ERROR_T D .RMS
- - - - ARIMA .MAX ······ LOAD_AVG .MAX - - - - ERROR_T D .MAX

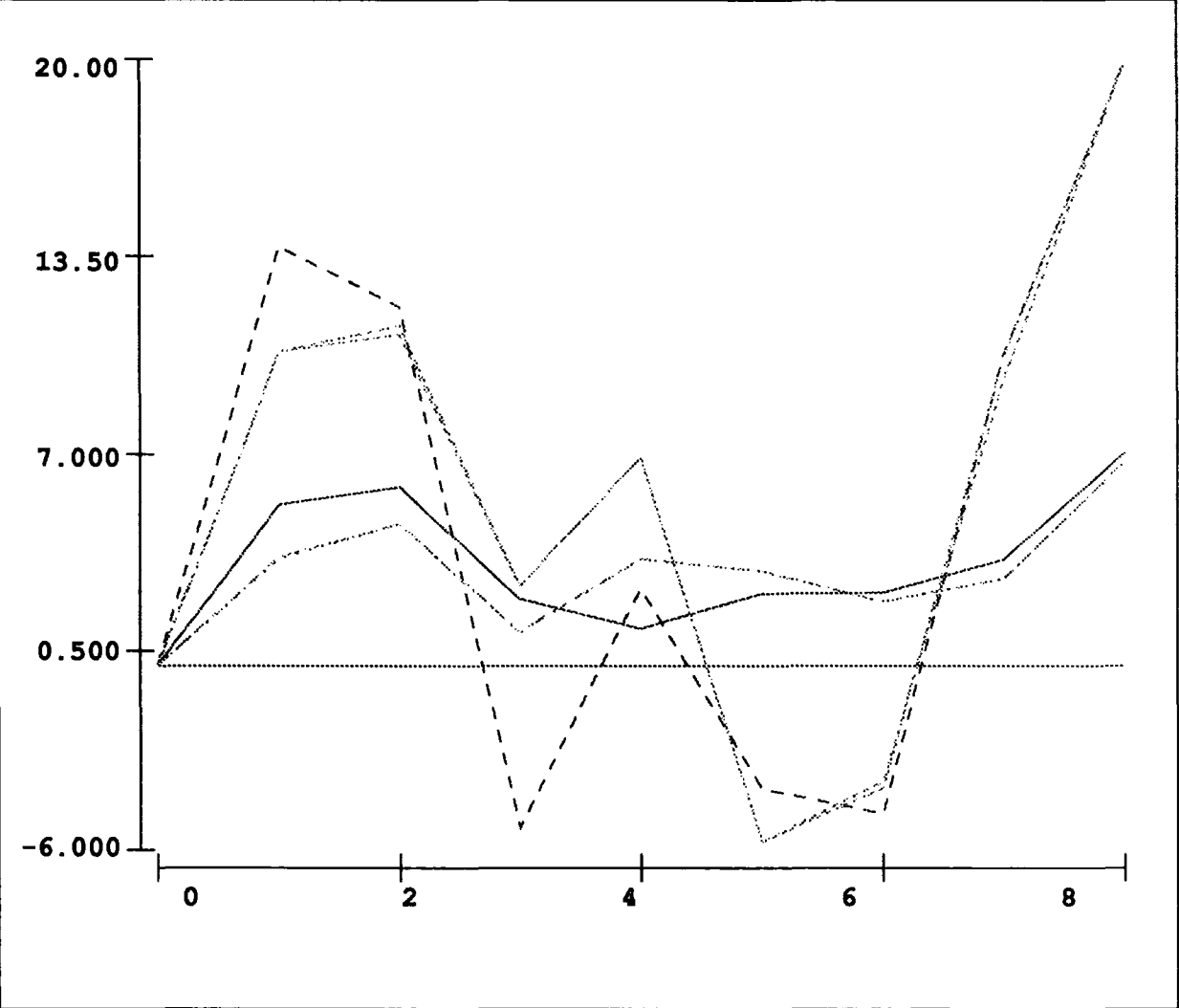


Figure 7.4 Comparison of ARIMA with Error-threshold-detection of Winter Weekends

**Table 7.7: Comparison of ARIMA with Error-threshold-detection
for
Summer Saturdays**

Date	Temp. °C	ARIMA(%)		Load-AVG(%)		Error-T-D(%)	
		R.M.S.	Max.	R.M.S.	Max.	R.M.S.	Max.
9/6/1984	23.3	4.43	9.05	6.52	12.62	6.52	12.62
16/6/1984	23.2	1.59	2.92	1.76	4.16	1.76	4.16
23/6/1984	19.7	2.53	-6.85	2.78	-7.06	2.67	-6.85
30/6/1984	19.4	2.92	8.05	1.75	4.38	1.73	4.38
7/7/1984	28.2	1.05	2.91	2.08	5.32	2.06	5.32
14/7/1984	19.9	2.74	-6.18	2.40	-5.60	2.60	-6.18
21/7/1984	27.3	2.97	5.35	1.77	3.22	1.81	3.44
28/7/1984	30.6	1.36	2.74	2.35	4.16	2.33	4.16
4/8/1984	19.8	3.17	-8.63	3.12	-8.50	3.20	-8.62
11/8/1984	23.1	2.33	-4.78	2.06	-4.78	2.12	-4.80
18/8/1984	25.9	2.28	-5.20	2.43	-5.20	2.45	-5.20
25/8/1984	23.7	1.29	-4.13	1.38	-5.63	1.43	-5.64

TITLE: Comparison of ARIMA with Error-threshold-detection

FIGURE: of Summer Saturdays

— ARIMA.RMS ······ LOAD_AVG.RMS - - - - - ERROR_T D.RMS
- - - - - ARIMA.MAX ······ LOAD_AVG.MAX - - - - - ERROR_T D.MAX

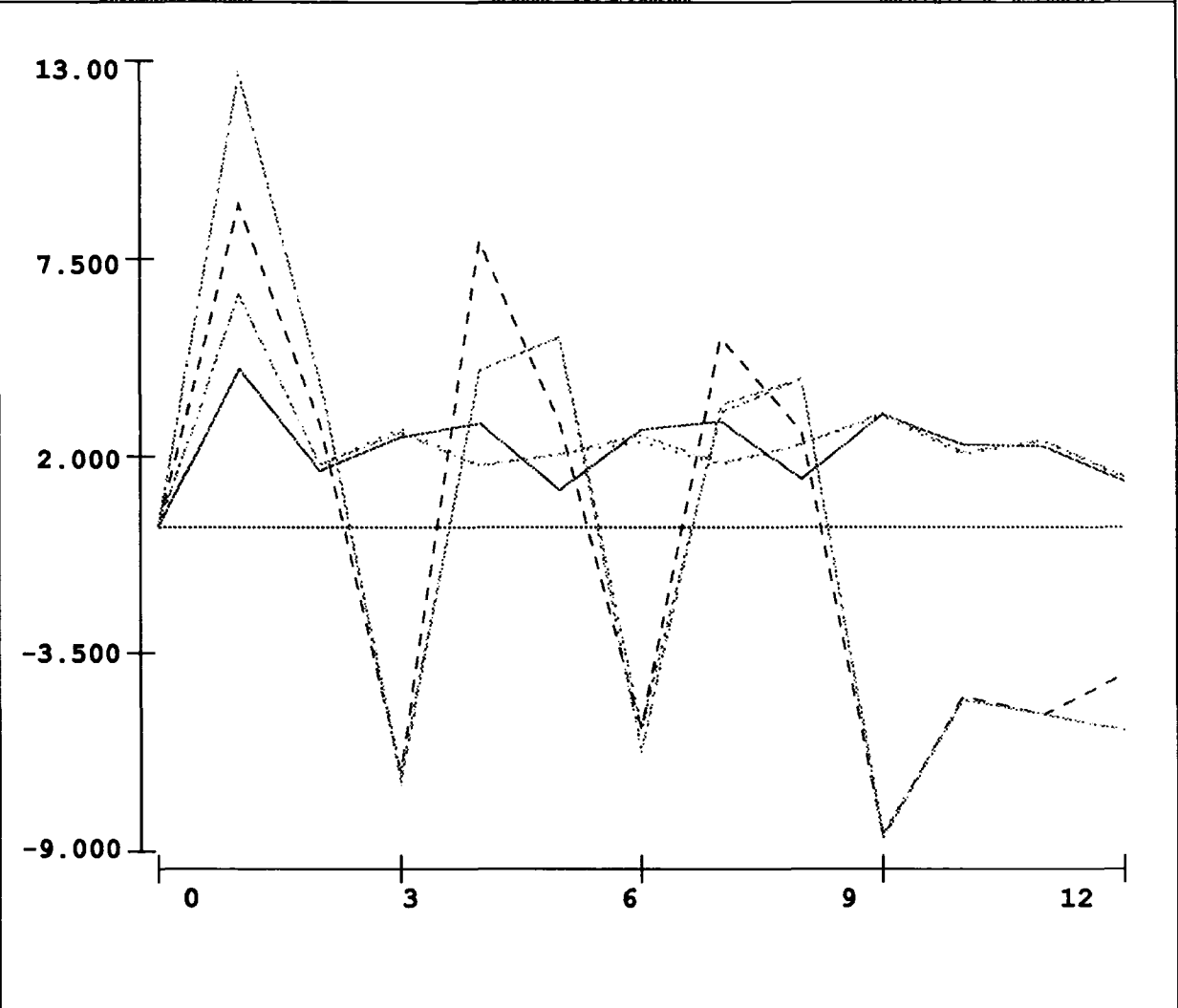


Figure 7.5 Comparison of ARIMA with Error-threshold-detection of Summer Saturdays

**Table 7.8: Comparison of ARIMA with Error-threshold-detection
for
Summer Sundays**

Date	Temp. °C	ARIMA(%)		Load-AVG(%)		Error-T-D(%)	
		R.M.S.	Max.	R.M.S.	Max.	R.M.S.	Max.
10/6/1984	24.6	4.14	8.43	5.60	11.59	5.59	11.59
17/6/1984	25.3	1.14	4.29	2.10	4.69	2.06	4.70
24/6/1984	18.3	2.67	-5.43	2.60	-4.68	2.61	-4.90
1/7/1984	21.9	2.14	4.73	1.30	3.26	1.34	3.26
8/7/1984	31.7	2.87	7.06	3.64	8.21	3.59	8.21
15/7/1984	18.9	3.76	-8.86	2.65	-5.78	2.72	-5.78
22/7/1984	25.8	5.16	8.64	3.70	5.55	3.75	5.55
29/7/1984	28.4	2.50	4.24	4.72	8.09	4.72	8.09
5/8/1984	19.8	4.81	-8.32	3.89	-7.46	3.92	-8.12
12/8/1984	23.6	1.87	-4.41	2.43	-8.25	2.41	-8.25
19/8/1984	28.8	1.61	3.40	2.24	-5.12	2.17	-5.13
26/8/1984	23.5	2.27	6.07	2.30	6.07	2.28	6.07

TITLE: Comparison of ARIMA with Error-threshold-detection

FIGURE: of Summer Sundays

— ARIMA.RMS ······ LOAD_AVG.RMS - - - - - ERROR_T D.RMS
- - - - - ARIMA.MAX ······ LOAD_AVG.MAX ······ ERROR_T D.MAX

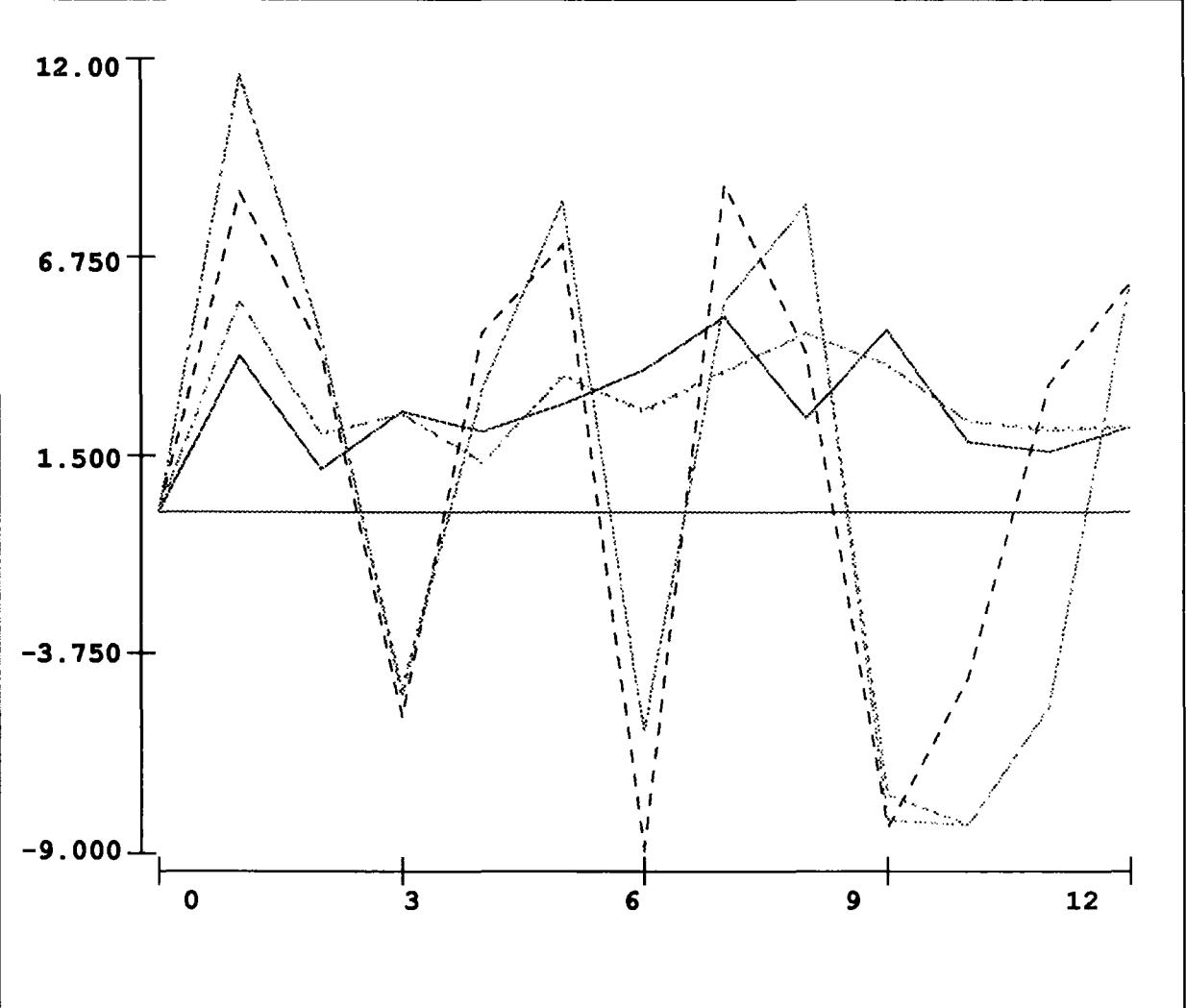


Figure 7.6 Comparison of ARIMA with Error-threshold-detection of Summer Sundays

From Tables 7.5 to 7.8, it can be seen that this modification with error threshold detection is really a compromise between ARIMA and the simplified modification, even though it performs better for some special days. There are some problems associated with the modification, one of which is that, if it is used for on-line prediction, what threshold should be chosen? Should it be chosen off-line and kept constant on-line, or changed dynamically? The application of the modification will, of course, result in a number of practical problems.

For both kinds of modifications, the actual effect of weather conditions is not really captured. As the ARIMA model has proved [79], the biggest errors usually occur around the time of midday, and the weather factor which would affect the load demand at that moment is the maximum temperature on the day. The maximum temperature is therefore thought to be the most important factor in causing prediction errors under normal circumstances. It is intuitively quite straightforward to determine the load change trend when the temperature change trend is known.

Considering Table 7.7, if maximum temperatures change monotonically on the days of which the recorded load data are used for prediction, then the univariate ARIMA gives better results than that from the modified approaches. For example, to predict load for the date of 28/7/1984 and 18/8/1984, the maximum temperatures increase gradually from 19.9°C and 19.8°C in the last days-of-week and to 30.6°C and 25.9°C on the current days respectively, the decreased loads, caused from the increasing temperatures, can be predicted by ARIMA implicitly. So predictions are good with R.M.S. errors of 1.36 % and 2.28 % only. However, for the date of 4/8/1984, the maximum temperatures do not change monotonically. There is an increase from 27.3°C to 30.6 °C, then a dramatic decrease to 19.8 °C for the current day. In this case, the ARIMA model cannot eliminate the load variation caused by the effect of weather conditions. Thus, prediction error is as high as 3.17 %. Similar examples can be found for Sundays in Table 7.8.

**Table 7.9: Comparison of ARIMA with Combined Prediction
for
Winter Saturdays**

Date	Temp. °C	ARIMA(%)		Load-AVG(%)		Combined-P(%)	
		R.M.S.	Max.	R.M.S.	Max.	R.M.S.	Max.
3/3/1984	8.0	5.34	13.81	3.57	10.35	3.57	10.35
10/3/1984	8.1	2.22	-5.27	1.11	2.66	2.22	-5.27
17/10/1984	5.8	2.39	-4.01	3.15	-5.73	3.15	-5.73
24/3/1984	7.9	3.53	10.21	2.89	9.41	2.89	9.41

**Table 7.10: Comparison of ARIMA with Combined Prediction
for
Winter Sundays**

Date	Temp. °C	ARIMA(%)		Load-AVG(%)		Combined-P(%)	
		R.M.S.	Max.	R.M.S.	Max.	R.M.S.	Max.
4/3/1984	7.3	5.92	11.82	4.71	10.91	4.71	10.91
11/3/1984	10.5	1.23	2.56	3.56	6.89	1.23	2.56
18/10/1984	5.8	2.42	-4.82	2.12	-3.78	2.12	-3.78
25/3/1984	7.8	7.07	19.85	6.75	19.89	6.75	19.89

TITLE: Comparison of ARIMA with Combined Prediction

FIGURE: of Winter Weekends

— ARIMA .RMS ······ LOAD_AVG.RMS - - - - - COMBINED_P.RMS
- - - - - ARIMA .MAX ······ LOAD_AVG.MAX - - - - - COMBINED_P.MAX

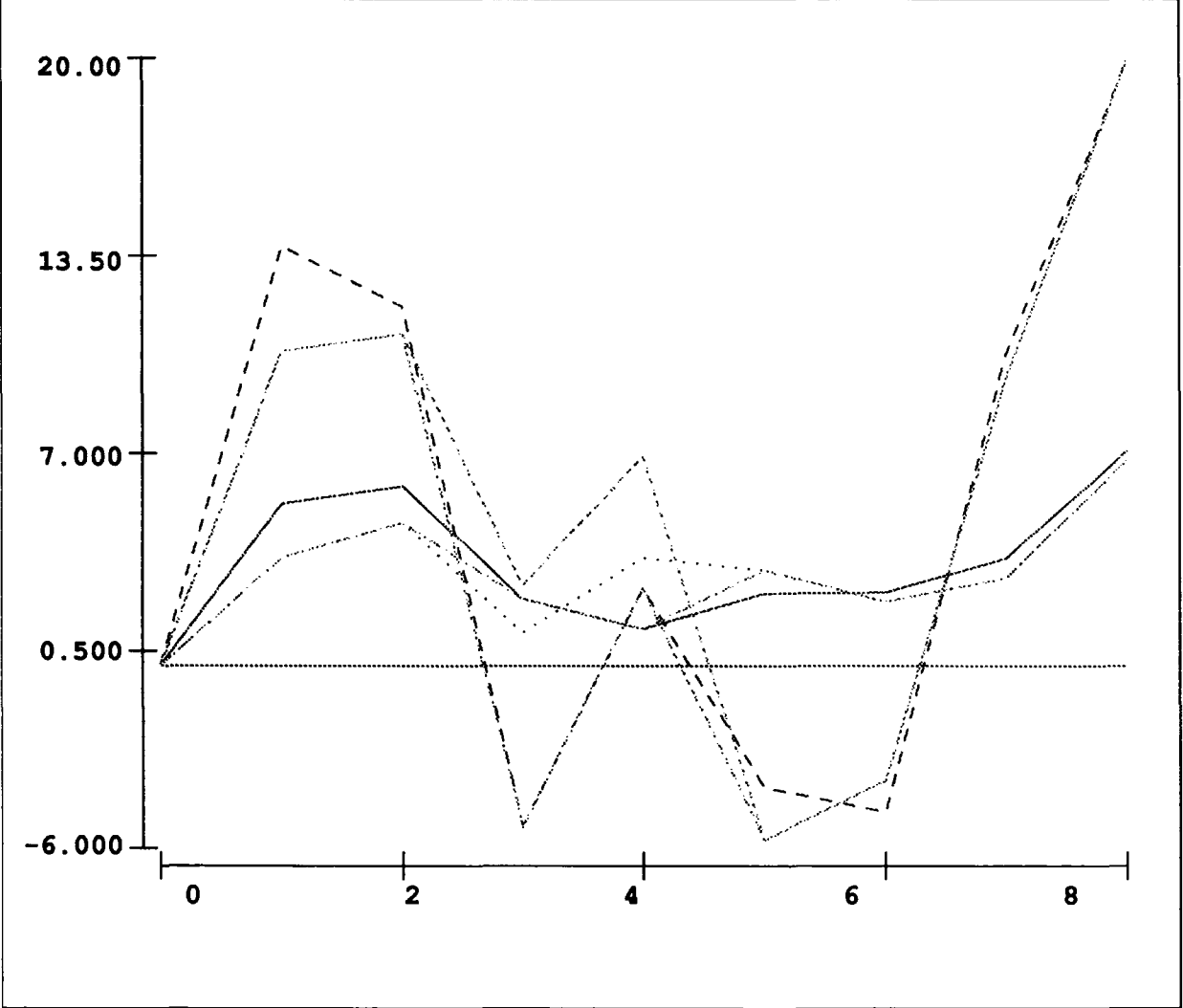
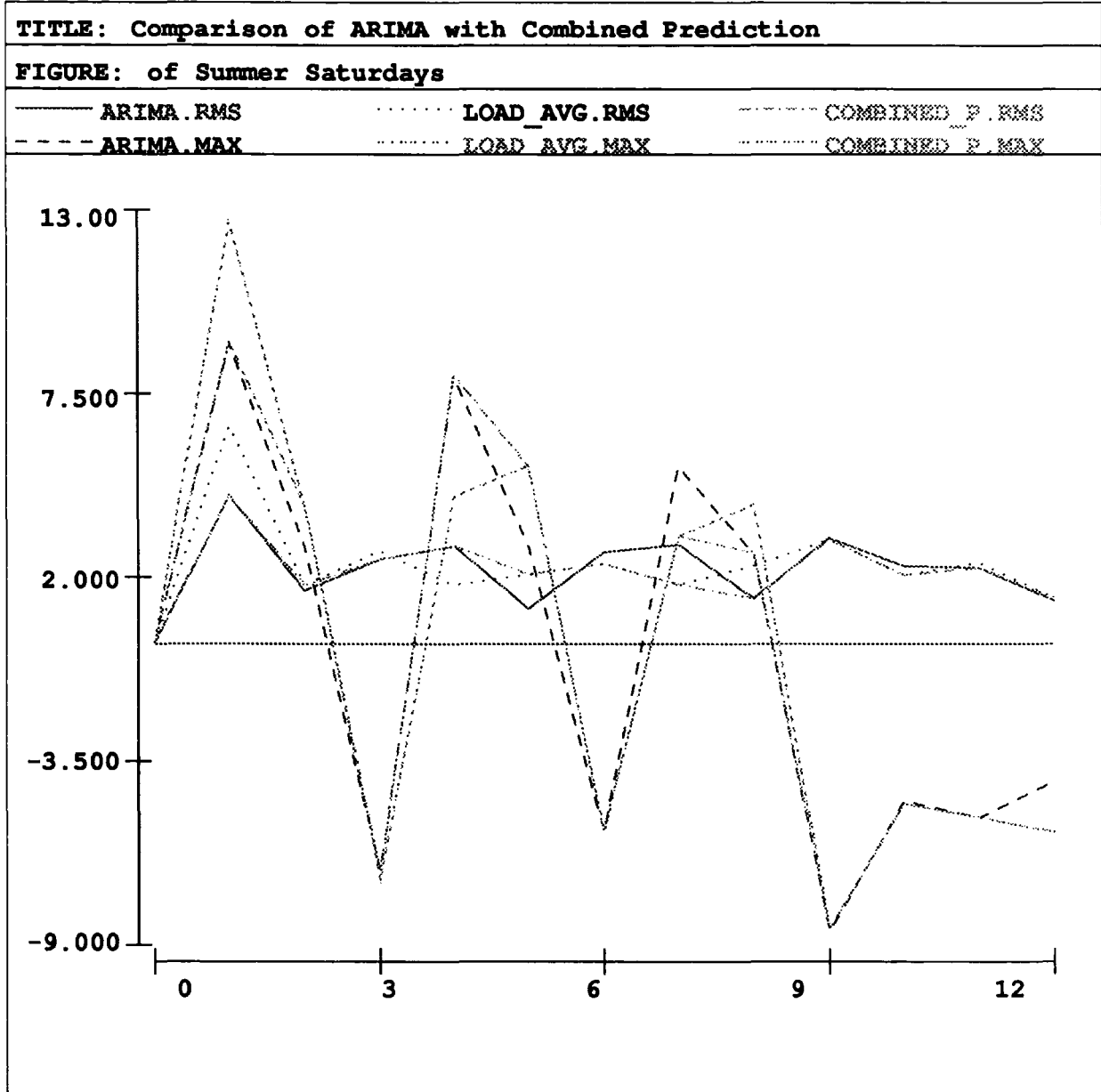


Figure 7.7 Comparison of ARIMA with Combined Prediction of Winter Weekends

**Table 7.11: Comparison of ARIMA with Combined Prediction
for
Summer Saturdays**

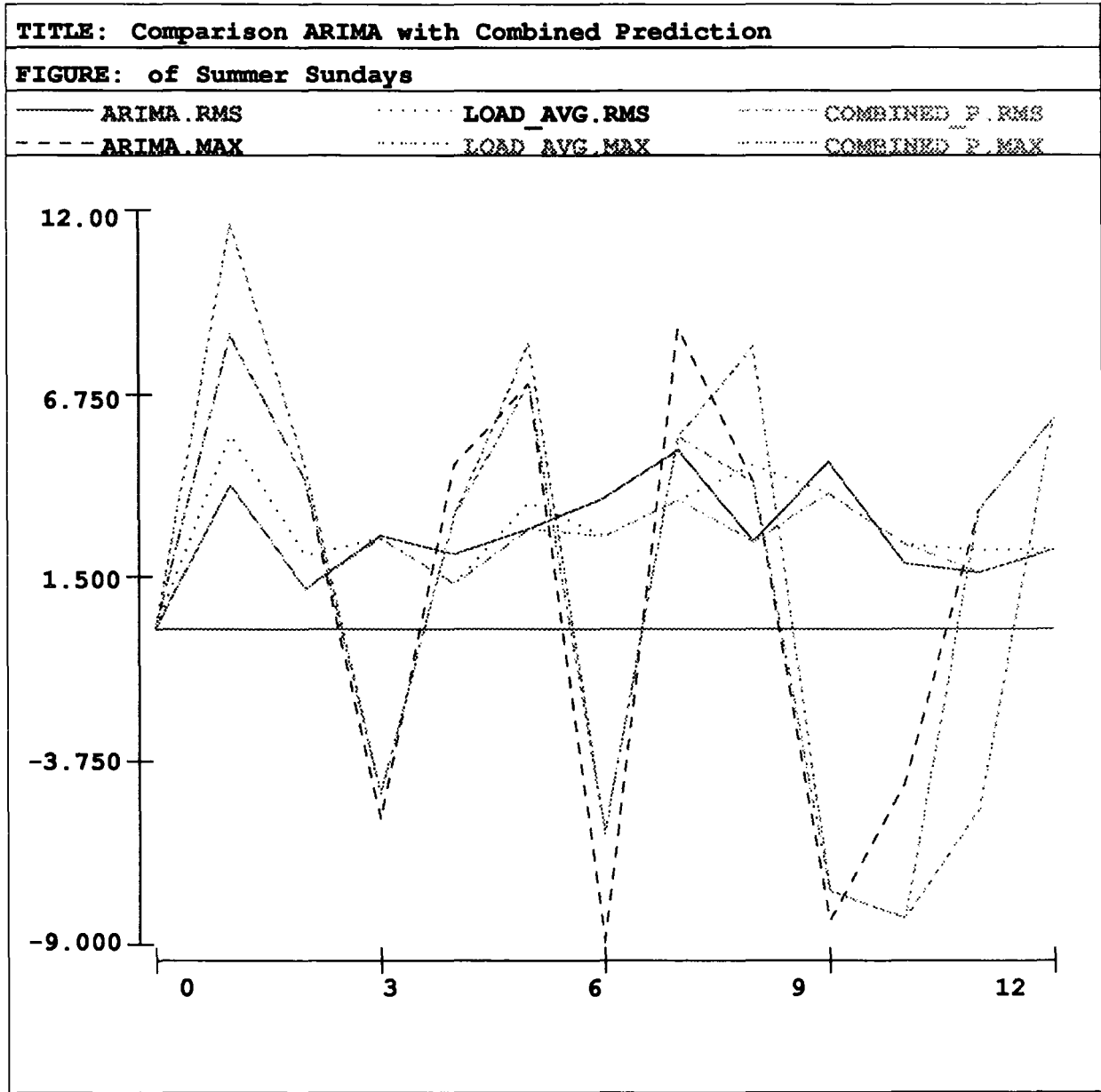
Date	Temp. °C	ARIMA(%)		Load-AVG(%)		Combined-P(%)	
		R.M.S.	Max.	R.M.S.	Max.	R.M.S.	Max.
9/6/1984	23.3	4.43	9.05	6.52	12.62	4.43	9.05
16/6/1984	23.2	1.59	2.92	1.76	4.16	1.76	4.16
23/6/1984	19.7	2.53	-6.85	2.78	-7.06	2.53	-6.85
30/6/1984	19.4	2.92	8.05	1.75	4.38	2.92	8.05
7/7/1984	28.2	1.05	2.91	2.08	5.32	2.08	5.32
14/7/1984	19.9	2.74	-6.18	2.40	-5.60	2.40	-5.60
21/7/1984	27.3	2.97	5.35	1.77	3.22	1.77	3.22
28/7/1984	30.6	1.36	2.74	2.35	4.16	1.36	2.74
4/8/1984	19.8	3.17	-8.63	3.12	-8.50	3.12	-8.50
11/8/1984	23.1	2.33	-4.78	2.06	-4.78	2.06	-4.78
18/8/1984	25.9	2.28	-5.20	2.43	-5.20	2.28	-5.20
25/8/1984	23.7	1.29	-4.13	1.38	-5.63	1.38	-5.63



**Figure 7.8 Comparison of ARIMA with Combined Prediction
of Summer Saturdays**

**Table 7.12: Comparison of ARIMA with Combined Prediction
for
Summer Sundays**

Date	Temp. °C	ARIMA(%)		Load-AVG(%)		Combined-P(%)	
		R.M.S.	Max.	R.M.S.	Max.	R.M.S.	Max.
10/6/1984	24.6	4.14	8.43	5.60	11.59	4.14	8.43
17/6/1984	25.3	1.14	4.29	2.10	4.69	1.14	4.29
24/6/1984	18.3	2.67	-5.43	2.60	-4.68	2.60	-4.68
1/7/1984	21.9	2.14	4.73	1.30	3.26	1.30	3.26
8/7/1984	31.7	2.87	7.06	3.64	8.21	2.87	7.06
15/7/1984	18.9	3.76	-8.86	2.65	-5.78	2.65	-5.78
22/7/1984	25.8	5.16	8.64	3.70	5.55	3.70	5.55
29/7/1984	28.4	2.50	4.24	4.72	8.09	2.50	4.24
5/8/1984	19.8	4.81	-8.32	3.89	-7.46	3.89	-7.46
12/8/1984	23.6	1.87	-4.41	2.43	-8.25	2.43	-8.25
19/8/1984	28.8	1.61	3.40	2.24	-5.12	1.61	3.40
26/8/1984	23.5	2.27	6.07	2.30	6.07	2.30	6.07



**Figure 7.9 Comparison of ARIMA with Combined Prediction
of Summer Sundays**

It is apparent that better prediction may be obtained if the maximum temperatures change monotonically from past days-of-week to the present day, then the real recorded load data can be directly used for prediction by the ARIMA. Otherwise the average of predicted load with actual load of the previous day-of-week is used to replace the actual load for that day in the ARIMA model. All these are written in the form of production rules in the prediction procedures. The results are presented in Tables 7.9 to 7.12.

There are some unexpected results in Table 7.11. One example is to predict load for the date of 30/6/1984. The R.M.S. error from the original ARIMA model is 2.92 % with a maximum error of 8.05 %, while the R.M.S. error from load averaging is 1.75 % with maximum error of only 4.38 %. If we examine the maximum temperature change trend, it is found that the maximum temperature of the previous day-of-week is only 19.7°C, which is much closer to 19.4°C of the predicted day, while the earlier maximum temperature is as high as 23.2°C. Because the prediction of load averaging stems from the average of predicted load which may be corresponding to 23°C approximately, and the actual load corresponding to 19.7°C; the temperature corresponding to this averaged load may be better located between 23.2°C and 19.4°C than 19.7°C. A similar explanation may also be given for the result of date 10/3/1984 in Table 7.9, even though the difference is very slight.

This gives rise to the necessity of using the actual temperatures quantitatively, which is analysed in the next section.

7.7 Prediction by employing actual weather information

If we simplify the relationship between weather-sensitive load P_s and the temperature changes, as follows:

$$P_s(d, t) = g(t)(T(d, t) - T_N(d, t))$$

where:

$T(d,t)$ is the actual temperature at time t of day d ;

$T_N(d,t)$ is the expected temperature at time t of day d ;

$g(t)$ is a multiplicative factor to give the additional consumption due to temperature change (in MW/ $^{\circ}C$), referred to as load/temperature variation rate. The function $g(t)$ is calculated by dividing the load changes by the corresponding temperature changes.

Because only maximum temperature of a day is available, it is realised that T and T_N may not occur at the same time t . So, $g(t)$ is the average load/temperature variation rate. In addition, the life-style may be different from one day to another, $g(t)$ can be different on Saturday from on Sunday. So, calculation of $g(t)$ is simply based on the load and temperature differences of the same days-of-week of two adjacent weeks.

There is a rule applied in the adjustment of $g(t)$. Namely, the load change rate over temperature $g(t)$ should be negative, which means:

- 1) a positive load difference if the temperature difference is negative;
- 2) a negative load difference if the temperature difference is positive;

The reason is that, if temperature goes high (positive temperature difference), less electricity is needed for heating, and the whole load decreases (negative load changes); and, if temperature drops, an increasing load will be observed. So, the load/temperature variation rate, which is calculated from the past load and weather data, should be set to zero or an appropriate negative value if it is positive.

Since there are measurement errors in both load data and temperatures, and sometimes the consumers are not so sensitive to slight changes of weather conditions. That means if temperature changes slightly, weather-sensitive load variation can be ignored. A temperature change threshold can probably be used to take this into account. Since the temperature change is calculated in the following way:

$$d(T) = |T_1 - T_2|,$$

the following rule can be applied:

If $d(T) \leq 1.0$, then no adjustment is needed for the variation of load because T_2 is nearly the same as T_1 .

Here, 1.0 is referred to the temperature threshold.

It might be necessary to set different temperature thresholds for different seasons because of the different sensitivity of weather-dependent load to weather changes. In spring, consumers are more sensitive to weather changes than in summer, so a lower temperature threshold can be used in spring than in summer.

Thus, the past load data can be converted by adjusting weather-sensitive load, to match the weather conditions which follow a smooth trend with that of the present day.

Testing results are listed in Tables 7.13 to 7.16 in which 1.0°C and 1.5°C are chosen as temperature thresholds for spring and summer seasons respectively.

It is apparent from the tables that the performance of modification 3 ("weather") is on the whole better than that of the ARIMA, especially for the cases in which temperatures change irregularly. For example, to predict the load for the date of 21/7/1984, the maximum temperatures change from 28.2°C to 19.9°C in the previous two weeks, and then to 27.3°C of the present day, the recorded load for date of 14/7/1984 is adjusted so that it corresponds to the temperature in the middle point of 28.2°C and 27.3°C , i.e., 27.7°C . The load change rate over the temperature $g(t)$ is simply determined by the load variation over temperature changes from 7/7/1984 to 14/7/1984.

**Table 7.13: Comparison of ARIMA with Weather-consideration
for
Winter Saturdays**

Date	Temp. °C	ARIMA(%)		Weather(%)	
		R.M.S.	Max.	R.M.S.	Max
3/3/1984	8.0	5.34	13.81	3.21	10.11
10/3/1984	8.1	2.22	-5.27	1.28	-2.74
17/3/1984	5.8	2.39	-4.01	2.39	-4.01
24/3/1984	7.9	3.53	10.21	2.73	8.95

**Table 7.14: Comparison of ARIMA with Weather-consideration
for
Winter Sundays**

Date	Temp. °C	ARIMA(%)		Weather(%)	
		R.M.S.	Max.	R.M.S.	Max
4/3/1984	7.3	5.92	11.82	5.92	11.82
11/3/1984	10.5	1.23	2.56	1.34	2.89
18/3/1984	5.8	2.42	-4.82	1.27	3.54
25/3/1984	7.8	7.07	19.85	6.48	19.88

TITLE: Comparison of ARIMA with Weather Consideration

FIGURE: of Winter Weekends

— ARIMA.RMS ····· WEATHER.RMS
- - - ARIMA.MAX ····· WEATHER.MAX

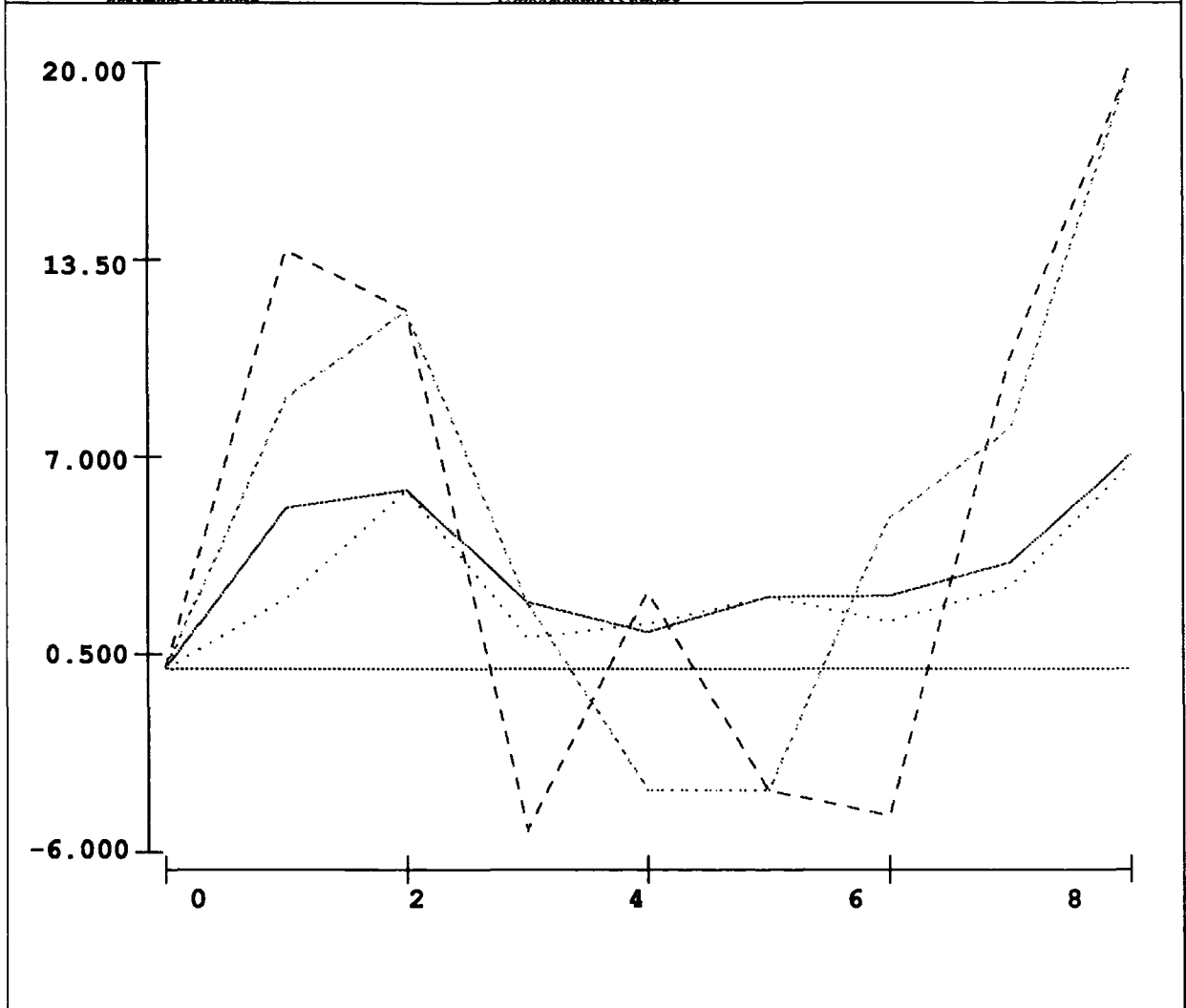
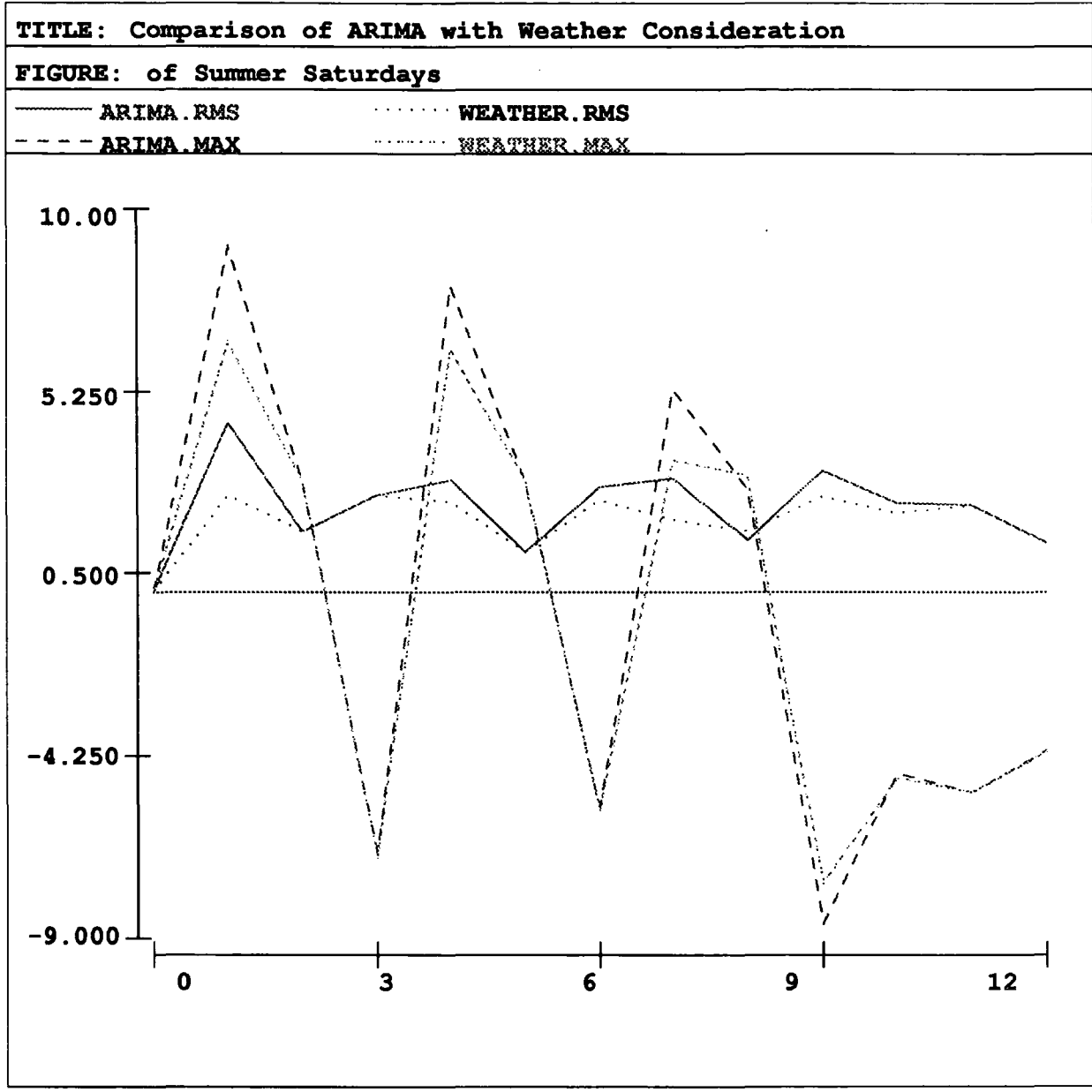


Figure 7.10 Comparison of ARIMA with Weather Consideration of Winter Weekends

**Table 7.15: Comparison of ARIMA with Weather-consideration
for
Summer Saturdays**

Date	Temp. °C	ARIMA(%)		Weather(%)	
		R.M.S.	Max.	R.M.S.	Max
9/6/1984	23.3	4.43	9.05	4.20	8.65
16/6/1984	23.2	1.59	2.92	1.34	2.92
23/6/1984	19.7	2.53	-6.85	2.53	-6.85
30/6/1984	19.4	2.92	8.05	2.35	6.36
7/7/1984	28.2	1.05	2.91	1.05	2.91
14/7/1984	19.9	2.74	-6.18	2.41	-5.62
21/7/1984	27.3	2.97	5.35	1.91	3.46
28/7/1984	30.6	1.36	2.74	1.59	3.06
4/8/1984	19.8	3.17	-8.63	2.47	-7.56
11/8/1984	23.1	2.33	-4.78	2.09	-4.80
18/8/1984	25.9	2.28	-5.20	2.28	-5.20
25/8/1984	23.7	1.29	-4.13	1.29	-4.13



**Figure 7.11 Comparison of ARIMA with Weather Consideration
of Summer Saturdays**

**Table 7.16: Comparison of ARIMA with Weather-consideration
for
Summer Sundays**

Date	Temp. °C	ARIMA(%)		Weather(%)	
		R.M.S.	Max.	R.M.S.	Max
10/6/1984	24.6	4.14	8.43	3.46	6.84
17/6/1984	25.3	1.14	4.29	1.59	5.03
24/6/1984	18.3	2.67	-5.43	2.67	-5.43
1/7/1984	21.9	2.14	4.73	1.44	3.56
8/7/1984	31.7	2.87	7.06	2.38	6.04
15/7/1984	18.9	3.76	-8.86	2.50	-5.47
22/7/1984	25.8	5.16	8.64	4.07	6.05
29/7/1984	28.4	2.50	4.24	3.12	5.49
5/8/1984	19.8	4.81	-8.32	2.86	-6.37
12/8/1984	23.6	1.87	-4.41	2.00	-7.28
19/8/1984	28.8	1.61	3.40	1.61	3.40
26/8/1984	23.5	2.27	6.07	2.34	6.07

TITLE: Comparison of ARIMA with Weather Consideration

FIGURE: of Summer Sundays

— ARIMA.RMS ····· WEATHER.RMS
- - - ARIMA.MAX ····· WEATHER.MAX

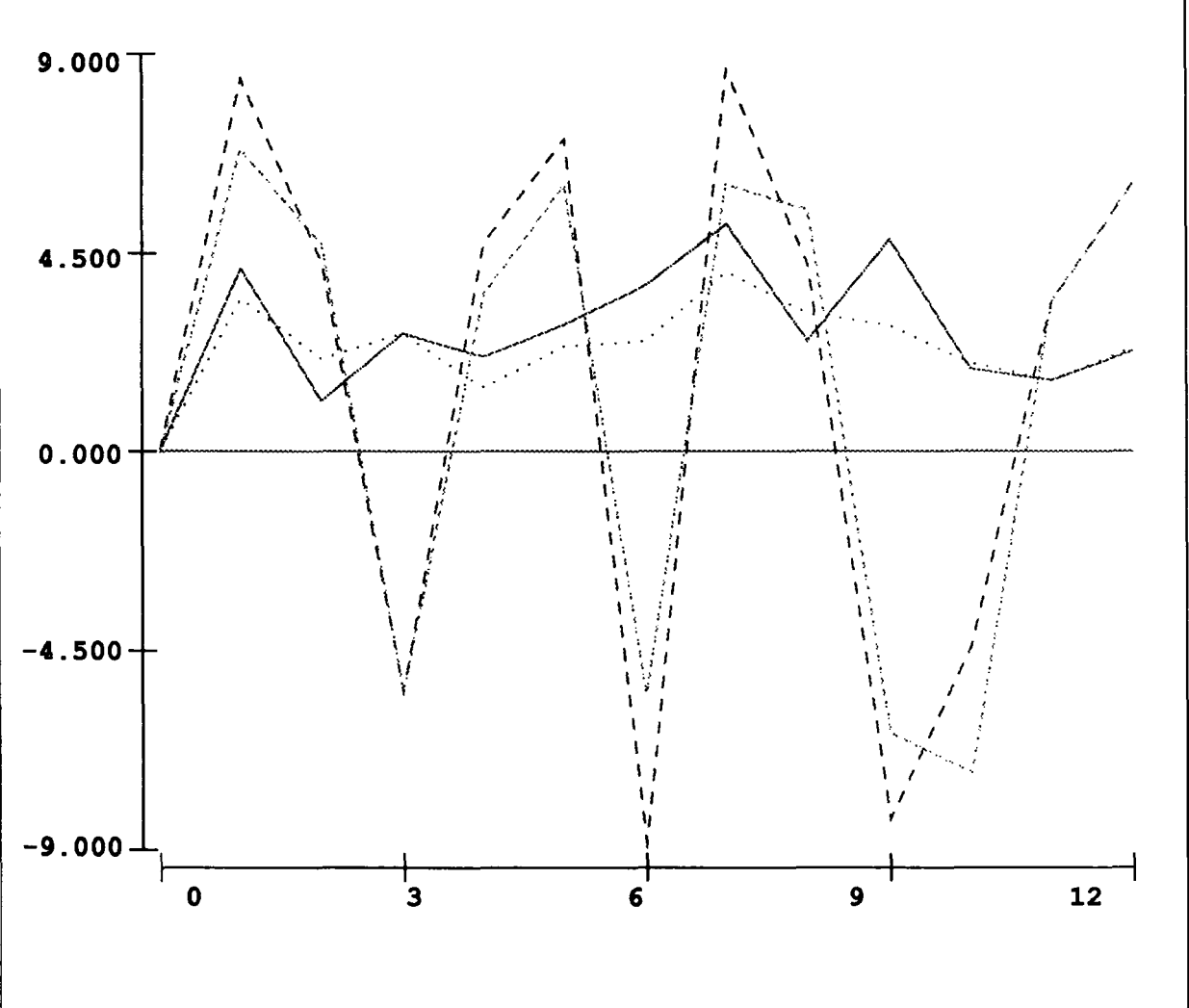


Figure 7.12 Comparison of ARIMA with Weather Consideration of Summer Sundays

It is concluded that the general prediction should be performed with the use of the following production rule as:

If the temperatures change monotonically, then the real load data are directly used to predict by ARIMA. If not, actual load should be replaced by the artificial load which corresponds to the natural weather changes.

7.8 Discussion and conclusion

A new approach has been presented in this chapter that takes weather effects into a univariate ARIMA model. The recorded historical load data have been modified with the weather information (historical and present) by the knowledge based system. Load prediction is made by the ARIMA model based on modified historical load. The analysis and testing show that weather has a significant influence on electrical loads, especially on the loads of weekends. But the effects of weather variables on load are complex, so, it is very difficult to express precisely the relationships between each weather variable and its corresponding components, unless each weather-dependent component, such as heating and lighting loads for each end-use, is measured and studied.

There is a time delay between the change of consumer's utilisation of electricity and the weather changes. The load changes reflecting weather changes are also influenced by some psychological factors, e.g., if the current day and the one preceding the day are cold days, more load may be needed for the current day than the load on the preceding day.

So, if all the contributing factors are known, good prediction may be expected. But, with the restriction that only the total load data of CEGB area and limited weather data recorded at Heathrow airport are available, some improvements can probably be obtained by taking the existing information into the well-developed univariate ARIMA model which has performed satisfactorily under normal situations.

Three modifications have been made to the historical load data. The first one is to take the average of predicted load and the actual load to replace the actual load for the same day-of-week in previous week. The second one is to use the error threshold to determine whether the actual load data should be modified or not. The third one is to use the load/temperature rate to modify the actual load data. Then the ARIMA model is used to predict weekend loads.

The ARIMA model gives good prediction results when the changes of contributing factors are in the same direction; Otherwise if the weather changes abruptly, the actual weather data have to be utilised to adjust the past loads.

When the maximum temperatures of the previous two Saturdays or Sundays and the present one do not decrease (or increase) monotonically or change irregularly, the recorded load of last Saturday or Sunday is replaced for further prediction by an artificial load which is corresponding to the weather conditions that make the weather condition change in one direction. The artificial load is obtained by modifying the actual load by the load/temperature variation rate which is calculated based on the earlier load and temperature data.

Production rules have been written to chose the appropriate modification to adjust the historical load data for prediction.

Although only the maximum temperature of 24 hours at Heathrow airport is used as the effective factor, the prediction seems promising. If more knowledge such as the load change rate per degree of temperature is obtained, better results can be expected. It is certain that if more weather information, which reflects the real weather conditions over the same area as the demand does, is available, then the actual influence of weather condition changes on electrical demand can be studied and the future demand can be estimated with better accuracy.

CHAPTER 8

CONCLUSION

8.1 Conclusion

This thesis has presented the results of a study of short-term load forecasting with special emphasis on special events by using knowledge based expert system. The investigation has been based on the CEGB system load.

Power system operation and control starts with load prediction which is to forecast electrical demand 2-4 hours or even days ahead in order to provide generation targets to power suppliers.

Although the recorded load data has been shown to be a random and stochastic process, the system load shows strong periodical components such as daily, weekly and seasonal cycles. The periodicity makes the load predictable. For the CEGB system load, the weekly cycle has been found to have a stronger effect than the daily cycle.

From the viewpoint of end-use, some part of the electricity is used for heating and lighting. So, any changes in weather conditions will definitely alter the use of electricity, and consequently, the load demand.

The most profound weather variables in the U.K. are the temperature and illumination conditions. Changes of these variables have been found to directly affect the electrical demand.

The commonly used methods for load prediction are based on the periodic characteristics of load demand and the causal effects of weather conditions. A

regression method is adopted to predict the weather-dependent load. The spectral expansion method can be used to extract the load variation due to weather influence by eigen-function and eigen-values. The pattern recognition method, on the other hand, classifies all the historical load records into appropriate classes according to their similar attributes. In practice, however, it can not be put into use because of the large proportion of misclassifications. In practice, the choice of a specific method is dependent upon considerations such as the required prediction accuracy, availability of input data, ease of application, and cost of adoption.

The ARIMA models (based on Box-Jenkin's time series analysis) have been shown to be the most suitable models for load forecasting. Since a proper ARIMA model can reflect the periodicity of the load demand, and have more weighting on the more recent loads, it can implicitly consider the weather influence on load. Many people have developed multi-variate ARIMA models of electrical demand and the influential factors. Unfortunately, the results showed not much improvement over the univariate model but more computation. The well-developed univariate ARIMA model with daily and weekly cycles can give a reasonable accuracy with acceptable computation time for predicting weekday loads. It can be adaptive without much human intervention, as opposed to the multi-variate model which needs regular inputs.

On the basis of the ARIMA model, this thesis has investigated to improve the load prediction of weekend loads which are often affected by weather condition changes. Due to limited available weather data, only the maximum temperatures of 24 hours have been used as the dominant variable. Instead of using a transfer function of temperature, some modification is made to the load data, which are used as a part of the historical data, only when the temperatures do not change in the same direction (monotonically). The load/temperature rate, which has been used to correct the load data corresponding to abnormal weather conditions, has been drawn from earlier load data and temperature data. After the load data have been corrected, the ARIMA model has been used to perform prediction. The results show some improvement over the original univariate ARIMA model on weekend load predictions.

When the time system changes from GMT to BST (or vice versa), the load demand has been shown not just to move forward or backward by one hour. In fact, the load shape has changed, especially around peak load time. The reason is that change of the time system has altered the life-style by one hour, but the load which was used for lighting does not follow the clock time very much. So, it has been shown necessary to disaggregate whole load into its components.

Based on the understanding about the usage of major consumers such as industrial, commercial, and domestic loads, as well as the sub-components, an appropriate curve is assigned to represent the demand for each component. As collecting the end-use load data for each component is a complex, time-consuming, and expensive process, disaggregation of the whole load into its composites has been found to be necessary in order to predict load around time change-overs. The study has applied the heuristic methods to disaggregate the overall load. Although there are no recorded data to validate the results of disaggregation, the curves obtained can be used for predicting the effects of time change-overs.

The approach proposed in this thesis for prediction of system load around time change-overs is based on the idea that the rest of load except the lighting load, which is assumed to be determined by sun-rise and sun-set time, is altered by one hour. By predicting the two parts separately, the effect of time change-overs can be forecast without the use of load data of previous years. This approach can be comparable with the most commonly used Relative Gap method.

Prediction of electrical load for public holidays is another problem. The usual mathematical model cannot accurately predict holiday loads, because there is not adequate historical load data within the time range of consideration. In England and Wales, the normal bank holidays are pre-determined on Mondays, and their load demand follows a similar pattern from year to year. Because of the load growth trend, it is not sufficient to simply use the recorded load data from previous years as the prediction. It has been observed that the

approach of using the preceding Saturday and Sunday loads to determine the load level, can improve the prediction accuracy over that obtained by using the historical holiday load data only. The approach can also take into consideration the weather effects on holiday loads. Difficulty is also found in predicting load for the special holidays such as Christmas Day and New Year's Day. Since the load level of the holiday will change according to the day-of-week on which the holiday is scheduled, knowledge about this is used to predict the load by production rules which take different corrective factors to modify the historical load depending on what days-of-week the holidays are. Much difficulty is involved in prediction of load for the period between Christmas Day and New Year's Day. During that period, load demand is totally governed by the number of people working on holidays. Prediction for this case must also be based on knowledge and expertise. It is dealt with by the approach which applies production rules to pick up appropriate reference loads and modify the loads.

Holiday effects are not only important in predicting the holiday load itself, but the recorded holiday load will also affect the model for further prediction after the holiday. It has been shown that the effect can be avoided by replacing the actual data by ordinary load data of the same day-of-week.

Therefore, as has been clearly shown in this thesis, the whole prediction procedure can be greatly improved by knowledge about the behaviour of the system load.

In conclusion, a good prediction needs enough information, data, and knowledge, as well as the application of a powerful computer. The knowledge based system can improve prediction performance of traditional mathematical methods.

8.2 Future work related to load prediction

This thesis represents a significant improvement of load prediction by combining knowledge with mathematical models. There is, however, much work

to do in the future which is related to load prediction.

As stated earlier, knowledge can improve the accuracy of load prediction, thus, more experience and knowledge can be acquired and obtained. For example, the television "pick-up" is still a problem to be solved. All the knowledge should be refined and improved. Better knowledge representation can also be investigated.

As to the mathematical model, a method can be developed to forecast the probability of the prediction as well as the probability of prediction errors. Both probabilities (or certainty factors) may be obtained by combining the probabilities of forecasting influential factors with the method.

It has been noticed that there is no perfect algorithm which can include all those causal factors, it may be sensible to apply appropriate knowledge to combine the prediction results from two or more methods.

Since the electrical load varies over the day, the week, and the seasons of a year, more and more attention has been paid to load management which attempts to "flatten" or "reshape" the load demand so that the overall operation is more economic. Load management is to monitor and control the use of some of the electrical utilisation so that the peak load can be reduced. One example is to use off-peak storage heating for domestic heating, for instance, the "economy 7" load in the U.K.. Spot pricing is another means to alter the use of electricity. As a result of implementation of tariffs and spot pricing, the overall load shape is influenced. So, in future work on load prediction, the effect of load management has to be included in the algorithm so that the result is much close to the actual demand.

REFERENCES & BIBLIOGRAPHY

- * 1. ABOU-HUSSEIN, M.S., KANDIL, M.S., TANTAWY, M.A., "An Accurate Model for Short-term Load Forecasting.", *IEEE Trans. on PAS-100*, No. 9, Vol. 100, Sept. 1981, pp. 4158 - 4165.
- * 2. ABU-EL-MAGD, M.A., SINHA, N.K., "Two New Algorithms for On-line Modelling and Forecasting of the Load Demand of a Multinode Power System.", *IEEE Trans. on PAS-100*, No. 7, Vol. 100, July 1981, pp. 3246 - 3253.
- * 3. ABU-EL-MAGD, M.A., SINHA, N.K. "Short-term Load Demand Modelling and Forecasting: A Review.", *IEEE Trans. on System, Man, and Cybernetics*, No. 3, Vol. 12, May/June 1982, pp. 370 - 382.
4. AIELLO, L., CECCHI, C. SARTINI, D., "Representation and Use of Meta-knowledge.", *Proceeding of the IEEE*, No. 10, Vol. 74, Oct. 1986, pp. 1304 - 1321.
5. AIZERMAN, M.A., BRAVERMAN, E.M., ROZONOER, L.I., "Theoretical Foundations of the Potential Function Method in Pattern Recognition Learning.", *UDC 62-507*, pp. 821 - 837.
- * 6. AKIMOTO, Y., TANAKA, H., YOSHIZAWA, J., KLAPPER, D.B., PRICE, W.W., WIRGAU, K.A., "Transient Stability Expert System.", *IEEE Trans. on Power Systems*, No. 1, Vol. 4, Feb. 1989, pp. 312 - 320.
7. ALLERA, S.V., MCGOWAN, J.E., "Medium-term Forecasts of Half-hourly System Demand: Development of an Interactive Demand Estimation Coefficient Model.", *IEE Proceedings Part C*, IEE No. 7, Vol. 133, Nov. 1986, pp. 393 - 396.
8. AMELINK, H., FORTE, A.M., GUBERMAN, R.P., "Dispatcher Alarm and Message Processing.", *IEEE Trans. on Power Systems*, No. 3, Vol. 1, Aug. 1986, pp. 188 - 194.

- ✧ 9. ANELLI, R., CAPRIO, U.D., MARCHESE, V., POZZI, S., "Short Term Prediction of Stationary Load Processes with a Correlation Function Finite Sum of Exponentials.", *7th. PSCC Lausanne*, pp. 401 – 408.
- 10. ANELLI, R., MAINI, M., MARCHESE, V., POZZI, S., "An On-line Procedure for Active Load Forecasting.", *7th. PSCC Lausanne*, pp. 573 – 580.
- 11. AZIT, A.H., SAIRAN, S.B., JASMON, G.B., "Feeder Load Analysis for Utility Demand Side Management.", *IEE Proceedings Part C*, IEE No. 5, Vol. 136, Sept. 1989, pp. 303 – 307.
- 12. BAJAK, S.V., "Long-Term Electricity Demand Forecasting Models: A Review of Methodologies.", *Electric Power Power Systems Research*, No. 1, Vol. 6, Jan. 1983, pp. 243 – 257.
- 13. BARAKAT, E.H., EISSA, M.A.M., "Forecasting Monthly Peak Demand in Fast Growing Electric Utility Using a Composite Multiregression-decomposition Model.", *IEE Proceedings Part C*, IEE No. 1, Vol. 136, Jan. 1989, pp. 35 – 41.
- 14. BARRETT, R., RAMSAY, A., SLOMAN, A., "POP-11: A Practical Language for Artificial Intelligence.", *Ellis Horwood Limited*, 1985.
- 15. BERRIE, T.W., "Power System Economics.", *Peter Peregrinus Ltd.*, 1983.
- ✧ 16. BJORK, C.O., KARLSSON, B.G., "Load Management Application for Industrial Loads.", *IEEE Trans. on PAS-104*, No. 8, Vol. 104, Aug. 1985, pp. 2058 – 2063.
- 17. BODGER, P.S., BROOKS, D.R.D., MOUTTER, S.P., "Spectral Decomposition of Variations in Electricity Loading Using Mixed Radix Fast Fourier Transform.", *IEE Proceedings Part C*, IEE No. 3, Vol. 134., May 1987, pp. 197 – 202.
- ✧ 18. BOLZERN, P., FRONZA, G., "Role of Weather Inputs in Short-term Forecasting of Electric Load.", *Electrical Power and Energy Systems*, No. 1, Vol. 8, Jan. 1986, pp. 42 – 46.

19. BORNARD, P., "Power System Protection and Substation Control: Trends, Opportunities and Problems.", *Electrical Power and Energy Systems*, No. 2, Vol. 10, April 1988, pp. 101 - 109.
- * 20. BOX, G.E.P., JENKINS, G.M., "Times Series Analysis - Forecasting and Control.", *Holen-Day*, 1970.
21. BRANDWAJN, V., TINNEY, W.F., "Generalised Method of Fault Analysis.", *IEEE Trans. on PAS-104*, No. 6, Vol. 104, June, 1985, pp. 1301 - 1306.
22. BREZILLON, P., FAUQUEMBERGUE, P., "SEPT, an Expert System Approach for the Monitoring of EHV Substation Control Equipment.", *Symposium on expert systems application to power systems, Stockholm-Helsinki, Aug. 22-26, 1988*, pp. 6-9 - 6-13.
- * 23. BROEHL, J.H., "An End-use Approach to Demand Forecasting.", *IEEE Trans. on PAS-100*, No. 6, Vol. 100, June 1981, pp. 2714 - 2718.
- * 24. BRUBACHER, S.R., WILSON, G.T., "Interpolating Time Series with Application to the Estimation of Holiday Effects on Electricity Demand.", *Appl. Statist.* No. 2, Vol. 25, 1976, pp. 107 - 116.
- * 25. BUCHANAN, B.G., SHORTLIFFE, E.H., "Rule-based Expert Systems.", *Addison-Wesley Publishing Company*, 1985.
26. BUCHANAN, S., TAYLOR, R., PAULOS, S., WARREN, W., HAY, J., "The Electricity Consumption Impacts of Commercial Energy Management Systems.", *IEEE Trans. on Power Systems*, No. 1, Vol. 4, Feb. 1989, pp. 213 - 219.
- * 27. BUNN, D.W., FARMER, E.D., "Comparative Models for Electrical Load Forecasting.", *John Wiley and Sons Ltd.*, 1985.
- * 28. BUN, D.W., SEIGAL, J.P., "Forecasting the Effects of Television Programming upon Electricity Loads.", *Journal of the Operational Research Society*, No. 1, Vol. 34, 1983, pp. 17 - 25.

- * 29. BUNN, D.W., "Short-term Forecasting: A Review of Procedures in the Electricity Supply Industry.", *Journal of the Operational Research Society*, No. 6, Vol. 33, pp. 533 - 545.
- * 30. BURTON, M., SHADBOLT, N., "POP-11 Programming for Artificial Intelligence.", *Addison-Wesley Publishing Company*, 1987.
- 31. CALLOWAY, T.M., BRICE III, C.W., "Physically-Based Model of Demand with Applications to Load Management Assessment and Load Forecasting.", *IEEE Trans. on PAS-101* No. 12, Vol. 101, Dec. 1982, pp. 4625 - 4631.
- * 32. CAMPO, R., RUIZ, P., "Adaptive Weather-sensitive Short Term Load Forecast.", *IEEE, Trans. on Power Systems*, No. 3, Vol. PWR5-2, Aug. 1987, pp. 592 - 600.
- * 33. CARDOZO, E., TALUKDAR, S.N., "A Distributed Expert System for Fault Diagnosis.", *IEEE Trans. on Power Systems*, NO. 2, Vol. 3, May 1988, pp. 641 - 646.
- 34. CEN, W.H., WU, C.L., "An Expert System in Nominal and Faulty Operation of Power System.", *Symposium on expert systems application to power systems, Stockholm-Helsinki, Aug. 22-26, 1988*, pp. 3-17 - 3-20.
- * 35. CHANG, C.S., "Fast Power System Voltage Prediction Using Knowledge-based Approach and On-line Box Data Creation.", *IEE Proceedings Part C*, IEE No. 2, Vol. 136, March 1989, pp. 87 - 99.
- * 36. CHATFIELD, C., PROTHERO, D.L., "Box-Jenkins Seasonal Forecasting: Problems in a Case-study.", *J. R. Statist. Soc. A*, Part 3, Vol. 136, 1973, pp. 295 - 336.
- 37. CHEN, C.S., YIN, P.J., WU, Y.C., "Load Forecasting for Substation in a Distribution System.", *Electric Power Power Systems Research*, No. 3, Vol. 16, May 1989, pp. 79 - 86.
- 38. CHEN, R.H., WANG, S.Y., XIANG, N.D., "Building Expert System for Static Security Assessment of Power System.", *Preprints of 1989 IFAC Symposium on Power Systems and Power Plant Control, Korea*, pp. 702 - 707.

- ✧ 39. CHENG, S.J., MALIK, O.P., HOPE, G.S., "An Expert system for Voltage and Reactive Power Control of a Power System.", *IEEE Trans. on Power Systems*, NO. 4, Vol. 3, Nov. 1988, pp. 1449 – 1455.
- 40. CHENG, S.J., MALIK, O.P., HOPE, G.S., "A Data Base Management System and its Application in a Voltage and Reactive Power Control Expert System.", *Electric Power Power Systems Research*, No. 2, Vol. 16, March 1989, pp. 147 – 155.
- ✧ 41. CHRISTIAANSE, W.R., "Short-term Load Forecasting Using General Exponential Smoothing.", *IEEE Trans. on PAS-90*, No. 2, Vol. 90, March/April, 1971, pp. 900 – 910.
- 42. CHRISTIE, R.D., TALUKDAR, S.N., "Expert Systems for On-line Security Assessment, A Preliminary Design.", *IEEE Trans. on Power Systems*, No. 2, Vol. 3, May 1988, pp. 654 – 659.
- 43. CHUI, D.K.H., "Artificial Intelligence Techniques for Power System Decision Problems.", *University of London*, Ph.D thesis, 1988.
- ✧ 44. CLEMENTS, K.A., WOOD, A.J., "Error Analysis of Econometric Load Forecasting Models.", *IEEE Trans. on PAS-98*, No. 2, Vol. 98, March/April 1979, pp. 393 – 399.
- 45. COMERFORD, R.B., GELLINGS, C.W., "The Application of Classical Forecasting Techniques to Load Management.", *IEEE Trans. on PAS-101*, No. 2, Vol. 101, Dec. 1982, pp. 4656 – 4664.
- ✧ 46. COMPUTER AND CONTROL DIVISION, "Modern Forecasting Methods.", *IEE Colloquium*, Digest No: 1986/119.
- ✧ 47. CORPENING, S.L., REPPEN, N.D., RINGLEE, R.J., "Experience with Weather-sensitive Load Models for Short and Long Term Forecasting.", *IEEE Trans. on PAS-92*, No. 6, Vol. 92, Nov./Dec. 1973, pp. 1966 – 1972.
- 48. DAMBORG, M.J., CHEN, M., "An Example of Integrating an Expert System into a Control Centre Using a Dispatcher Training Simulator.", *Symposium on expert systems application to power systems, Stockholm-Helsinki, Aug. 22-26, 1988*, pp. 3-21 – 3-26.

49. DAVEY, J., SASCKS, J.J., GUNNINGHAM, G.W., PRIEST, K.W., "Practical Application of Weather-sensitive Load Forecasting to System Planning.", *IEEE Trans. on PAS-92*, No.3, Vol. 92, May/June, 1973, pp. 971 - 977.
50. DAVID, A.K., "Load Forecasting under Spot Pricing.", *IEE Proceedings Part C*, IEE No. 5, Vol. 135, Sept. 1988, pp. 369 - 377.
51. DAVID, A.K., "Optimal Consumer Response for Electricity Spot Pricing.", *IEE Proceedings Part C*, IEE No. 5, Vol. 135, Sept. 1988, pp. 378 - 384.
52. DAVID, A.K., NUTT, D.J., CHANG, C.S., LEE, Y.C., "The Variation of Electricity Prices in Response to Supply - Demand Conditions and Devices for Consumer Interaction.", *Electrical Power and Energy Systems*, Vol. 8, No.2, April 1986, pp. 101 - 114.
53. DAVID, A.K., ZHAO, R.D., "Integrating Expert Systems with Dynamic Programming in Generation Expansion Planning.", *IEEE Trans. on Power Systems*, No. 3, Vol. 4, Aug. 1989, pp. 1095 - 1101.
- ✧ 54. DAVIES, M., "The Relationship Between Weather and Electricity Demand.", *The Institution of Electrical Engineers*, Vol. 106C, Oct. 1958, pp. 27 - 37.
- ✧ 55. DAVIES, M., "Techniques for Prediction in the Electricity-supply Industry and Developments of On-line Load-prediction Techniques with Results from Trials in the Southwest Region of the CEGB.", *IEE Proceedings Part C*, IEE No. 4, Vol. 117, April 1970.
56. DAVIS, M.W., KRUPA, T.J., DIEDZIC, M.J., "The Economics of Direct Control of Residential Loads on the Design and Operation of the Distribution System: Part II: Load Characteristics.", *IEEE Trans. on PAS-102*, No. 3, Vol. 102, March 1983, pp. 654 - 665.
57. DEBS, A.S. "Modern Power Systems Control and Operation.", *Kluwer Academic Publishers*, 1988.
- ✧ 58. DEHDASHTI, A.S., TUDOR, J.R., SMITH, M.C., "Forecasting of Hourly Load by Pattern Recognition. A Deterministic Approach.", *IEEE Trans. on PAS-101*, No. 9, Vol. 101, Sept. 1982, pp. 3290 - 3294.

59. DELGADO, R.M., "Demand-Side Management Alternatives.", *Proceeding of the IEEE*, No. 10, Vol. 73, Oct. 1985, pp. 1571 – 1488.
- * 60. DIJK, H.E., WEEGEN, A.W., ROELOFS, G.P.T., "An Expert System for Power System Restoration: Restoration Strategies.", *Symposium on expert systems application to power systems, Stockholm-Helsinki, Aug. 22-26, 1988*, pp. 8-9 – 8-16.
- * 61. DILLON, T.S., "Expert Systems: Potential and Limitations in the Application to Power Systems.", *Symposium on expert systems application to power systems, Stockholm-Helsinki, Aug. 22-26, 1988*, pp. 18-1 – 18-9.
62. DINSDALE, J.W., "Computer Based Substation Automation Control.", *Preprints of 1989 IFAC Symposium on Power Systems and Power Plant Control, Korea*, pp. 129 – 133.
- * 63. DODDS, G.I., IRWIN, G.W., BEATTIE, W.C., "Electricity Demand Modelling from Disaggregate Data.", *Electrical Power and Energy Systems*, Vol. 12, No. 1, Jan. 1990, pp. 50 – 60.
- * 64. DRYAR, H.A., "The Effect of Weather on the System Load.", *AIEE Trans.*, Vol. 63, 1944, pp. 1006 – 1013.
- * 65. ERNOULT, M., MATTATIA, R., "Short Term Load Forecasting: New Developments at the E.D.F.", *8th. PSCC Helsinki*, pp. 369 – 375.
- * 66. ERNOULT, M., MATTATIA, R., MESLIER, F., RABUT, P., "Estimation of the Sensitivity of the Electrical Energy Demand to Variations in Meteorological Conditions.", *Electrical Power and Energy Systems*, Vol. 5, No. 3, July 1983, pp. 189 – 198.
- * 67. FANKHAUSER, H.R., "A Novel Approach to On-line Short- and Intermediate-Term Load Forecasting.", *8th. PSCC Helsinki*, pp. 376 – 380.
68. FANKHAUSER, H.R., LITSGARD, M., "Error Limits and On-line Monitoring of Short-term Load Forecasts.", *9th. PSCC Portugal*, pp. 376 – 380.

- * 69. FARMER, E.D., "A Method of Prediction for Non-stationary Process and its Application to the Problem of Load Estimation.", *IFAC 1969*, pp. 47 - 54.
- * 70. FARMER, E.D., "On-line Load Prediction.", *Central Electricity Research Laboratories, REF. RD/L/*, 1969.
- 71. FAWZI, T.H., ALI, K.F., EL-SOBKI, S.M., "A New Planning Model for Distribution Systems.", *IEEE Trans. on PAS-102*, No. 9, Vol. 102, Sept. 1983, pp. 3010 - 3017.
- 72. FERNANDO, K.V., NICHOLSON, H., "Two-dimensional Curve Fitting and Prediction Using Spectral Analysis.", *IEE Proceedings Part D*, IEE No. 5, Vol. 129, Sept. 1982, pp. 145 - 150.
- 73. FININ, T.W., "Interactive Classification: A Technique for Acquiring and Maintaining Knowledge Bases.", *Proceeding of the IEEE*, No. 10, Vol. 74, Oct. 1986, pp. 1414 - 1421.
- * 74. FORSYTH, R., "Expert System: Principles and Case Studies.", *Chapman and Hall Computing*, 1984.
- 75. FRANCISCO, D.FALIANA, "Identification of Stochastic Electric Load Models from Physical Data.",
- * 76. FU, S.T., "A Pragmatic Approach for Short-term Load Forecasting Using Learning-Regression Method.", *7th. PSCC Lausanne*, pp. 581 - 587.
- * 77. GALIANA, F.D., HANDSCHIN, E., FIECHTER, A., "Identification of Stochastic Electric Load Models from Physical Data.", *IEEE Trans. on Automatic Control*, No. 6, Vol. 10, Dec. 1974, pp. 887 - 893.
- 78. GALIANA, F.D., MCGILLIS, D., "Design of a Longitudinal EHV Transmission Network: A Knowledge-based Approach.", *Symposium on expert systems application to power systems, Stockholm-Helsinki, Aug. 22-26, 1988*, pp. 3-9 - 3-16.
- * 79. GANN, J.O., "On-line Consumer Demand Forecasting Using Adaptive Time Series Analysis.", *School of Engineering and Applied Science, University of Durham*.

- ✧ 80. GELLINGS, C.W., AYLOR, R.W., "Electric Load Curve Synthesis: A Computer Simulation of an Electric Utility Load Shape.", *IEEE Trans. on PAS-100*, No. 1, Vol. 100, Jan. 1981, pp. 60 - 65.
81. GERMOND, A., "An International Survey of the Present Status and the Perspective of Expert Systems on Power System Analysis and Techniques.", *ELECTRA, CIGRE*, No. 123, March 1989, pp. 72 - 93.
82. GIRGIS, A.A., LEE, L., MAKRAM, E.B., "Optimal Forecasting of Weekly Load and Temperature of a Substation.", *Electric Power Systems Research*, Vol. 18, Jan. 1990, pp. 169 - 174.
- ✧ 83. GOH, T.N., CHOI, S.S., CHEN, S.B., "Forecasting of Electricity Demand by End-use Characteristics.", *Electric Power Systems Research*, No. 1, Vol. 6, Jan. 1983, pp. 177 - 183.
84. GOH, T.N., CHOI, S.S., TAN, C.H., TAN, K.C., "A Comparative Study of Short-Term Forecasting of Energy and Peak Power Demand.", *Electric Power Systems Research*, No. 1, Vol. 5, March 1982, pp. 63 - 71.
- ✧ 85. GOH, T.N., ONG, H.L., LEE, Y.O., "A New Approach to Statistical Forecasting of Daily Peak Power Demand.", *Electric Power Systems Research*, No. 2, Vol. 10, March 1986, pp. 145 - 148.
86. GRANGER, C.W.J., NEWBOLD, P., "Forecasting Economic Time Series.", *Academic Press*, 1977.
87. GROSS, C.A., "Power System Analysis.", *John Wiley and Sons*, 1979.
- ✧ 88. GROSS, G., GALIANA, F.D., "Short-term Load Forecasting.", *Proceeding of the IEEE*, No. 12, Vol. 75, Dec. 1987, pp. 1558 - 1573.
89. GROSS, G., HONG, H.W., "A Two-step Compensation Method for Solving Short Circuit Problems.", *IEEE Trans. on PAS-101*, No. 6, Vol. 101, June, 1982, pp. 1322 - 1331.
90. GUO, Y.Z., GAO, S., YANG, Y.H., "An Diagnostic Expert System for High Voltage Breaker Faults.", *Preprints of 1989 IFAC Symposium on Power Systems and Power Plant Control, Korea*, pp. 689 - 692.

- * 91. GUPTA, P.C., "A Stochastic Approach to Peak Power-demand Forecasting in Electric Utility Systems.", *IEEE Trans. on PAS-90*, No. 3, Vol. 90, Mar./Apr. 1971, pp. 823 - 832.
- * 92. GUPTA, P.C., YAMADA, K., "Adaptive Short Term Forecasting of Hourly Load Using Weather Information.", *IEEE Trans. on PAS-91*, Vol. 91, Sept./Oct. 1972, pp. 2085 - 2094.
- 93. GUSEINOV, F.G., RAMAZANOV, K.N., "Of One Method for the Calculation of the Power Consumption Prediction by Employing the Macloren Series with Discrete Initial Information.", pp. 409 - 415.
- * 94. HAGAN, M.T., BEHR, S.M., "The Time Series Approach to Short Term Load Forecasting.", *IEEE Trans. on Power Systems*, No. 3, Vol. PWRS-2, Aug. 1987, pp. 785 - 791.
- 95. HATTA, M., SATOH, H., SERIZAWA, Y., "Application of the Expert System to the Determination of the Operational Coordination of Switch Gears and Power Fuses for Short Circuit Protection.", *Symposium on expert systems application to power systems, Stockholm-Helsinki, Aug. 22-26, 1988*, pp. 6-27 - 6-34.
- * 96. HAYES-ROTH, F., WATERMAN, D.A., LENAT, D.B., "Building Expert Systems.", *Addison-Wesley*. 1983.
- * 97. HEINEMANN, G.T., NORDMAN, D.A., PLANT, E.C, "The Relationship Between Summer Weather and Summer Loads: A Regression Analysis.", *IEEE Trans. on PAS-85*, No. 11, Vol. 85, Nov. 1966, pp. 1144 - 1154.
- 98. HEUCK, K., HUBER, A., REUTER, E., "Power System Simulator for Realistic Dispatcher Training.", *Preprints of 1989 IFAC Symposium on Power Systems and Power Plant Control, Korea*, pp. 449 - 453.
- * 99. HIETALA, J.J., RIEBS, R.E., "Load Management at a Medium-size Utility.", *IEEE Trans. on Power Systems*, No. 2, Vol. 5, May 1990, pp. 513 - 519.
- 100. HIPEL, K.W., MCLEOD, A.I., LENNOX, W.C., "Advances in Box-Jenkins Modelling, 1. Model Construction.", *Water Resources Research*, No. 3, Vol. 13, June 1977, pp. 567 - 586.

101. HIYAMA, T., "Rule-based Stabilizer for Multi-Machine Power System.", *IEEE Trans. on Power Systems*, No. 2, Vol. 5, May 1990, pp. 403 – 411.
102. HUBBARD, J.C., "Monitoring Electric Load Forecasts.", *IEEE Trans. on PAS-88*, No. 6, Vol. 88, June, 1969, pp. 779 – 801.
- * 103. HUBELE, N.F., CHENG, C.S., "Identification of Seasonal Short-Term Load Forecasting Models Using Statistical Decision Functions.", *IEEE Trans. on Power Systems*, No. 1, Vol. 5, Feb. 1990, pp. 40 – 45.
104. IRISARRI, G.D., WIDERGREN, S.E., YEHSAKUL, P.D., "On-line Load Forecasting for Energy Control Center Application.", *IEEE Trans. on PAS-101*, No. 1, Vol. 101, Jan. 1982, pp. 71 – 78.
105. ITO, S., HATA, I., MARUYAMA, A., KAWAKAMI, J., "Application of Expert System to 500 KV Substation Operation Guide System.", *Symposium on expert systems application to power systems, Stockholm-Helsinki, Aug. 22-26, 1988*, pp. 6-14 – 6-21.
- * 106. JABBOUR, K., RIVEROS, J.F.V., LANDSBERGEN, D., MEYER, W., "ALFA: Automated Load Forecasting Assistant.", *IEEE Trans. on Power Systems*, No. 3, Vol.3, Aug. 1988, pp. 908 – 914.
107. JAIN, R., "Decision-making in the Presence of Fuzzy Variables.", *IEEE Trans. on Systems, Man, and Cybernetics*, No. 10, Vol. 6, Oct. 1976, pp. 698 – 703.
108. JASKE, M.R. "An Evaluation of Alternative Load Measurement Frameworks for Resource Planning.", *IEEE Trans. on Power Systems*, No. 1, Vol. 4, Feb. 1989, pp. 305 – 311.
109. JONES, R.H., "Identification and Autoregressive Spectrum Estimation.", *IEEE Trans. on Automatic Control, AC-19*, No. 6, Vol. 19, Dec. 1974, pp. 894 – 898.
110. KAKIMOTO, N., EMOTO, M., HAYASHI, M., "An Application of Artificial Intelligence to Restoration of Bulk Power Systems.", *Symposium on expert systems application to power systems, Stockholm-Helsinki, Aug. 22-26, 1988*, pp. 8-17 – 8-23.

111. KALRA, P.K., EMMANUEL, P., "Requirements of the Knowledge Based System for HVDC Transmission System.", *Symposium on expert systems application to power systems, Stockholm-Helsinki, Aug. 22-26, 1988*, pp. 6-22 - 6-26.
112. KAYE, R.J., OUTHRED, H.R., "A Theory of Electricity Tariff Design for Optimal Operation and Investment.", *IEEE Trans. on Power Systems*, No. 2, Vol. 4, May 1989, pp. 606 - 613.
113. KEINOSUKE, MATSUMOTO, TOSHIAKI, SAKAGUCHI, TOMOOMI, WAKE, "Fault Diagnosis of a Power System Based on a Description of the Structure and Function of the Relay System.", *Expert System*, No. 3. Vol. 2, July 1985, pp. 134 - 138.
- * 114. KERONEN, J.J., "An Expert System Prototype for Event Diagnosis and Real-time Operation Planning in Power System Control.", *IEEE Trans. on Power Systems*, No. 2, Vol. 4, May 1989, pp. 544 - 550.
- * 115. KEYHANI, A., MIRI, S.M., "On-line Weather-sensitive and Industrial Group Bus Load Forecasting for Microprocessor-based Application.", *IEEE Trans. on Power Apparatus and Systems, PAS-102*, No. 12, Vol. 102, Dec. 1983, pp. 3868 - 3876.
- ‡ 116. KEYHANI, A., DANIELS, H., "Real Time Load Modelling Technique: An Application to Short Term Load Prediction.", 1974, pp. 132 - 136.
117. KHONG, V.H., BIGHAM, J., "A Prototype Expert System Shell for Industrial Control.", *Symposium on expert systems application to power systems, Stockholm-Helsinki, Aug. 22-26, 1988*, pp. 2-10 - 2-15.
118. KIM, H., KO, Y., SHON, S., "An Expert System for the Electric Power Distribution System Design.", *Preprints of 1989 IFAC Symposium on Power Systems and Power Plant Control, Korea*, pp. 991 - 996.
- * 119. KIRSCHEN, D.S., WOLLENBERG, B.F., IRISARRI, G.D., BANN, J.J., MILLER, B.N., "Artificial Intelligence Applications in an Energy Management System Environment.", *Symposium on expert systems application to power systems, Stockholm-Helsinki, Aug. 22-26, 1988*, pp. 17-1 - 17-6.

- ✧ 120. KIRSCHEN, D.S., WOLLENBERG, B.F., IRISARRI, G.D., BANN, J.J., MILLER, B.N., "Controlling Power Systems During Emergencies: The Role of Expert Systems.", *IEEE Computer Application in Power*, April 1989, pp. 41 - 45.
- 121. KŁOS, A., FRYDRYSZAK, M., "Knowledge Based System for Network Solution.", *Symposium on expert systems application to power systems, Stockholm-Helsinki, Aug. 22-26, 1988*, pp. 16-26 - 16-31.
- 122. KNIGHT, U.G., BOOTH, R.R., MALLARD, S.A., LEWIS, D.W., "Computers in Power System Planning.", *Proceeding of the IEEE*, No. 7, Vol. 62, July 1974, pp. 872 - 883.
- ✧ 123. KROGH, B., LLINAS, E.S., LESSER, D., "Design and Implementation of an On-line Forecasting Algorithm.", *IEEE Trans. on PAS-101*, No. 9, Vol. 101, Sept. 1982, pp. 3284 - 3289.
- ✧ 124. KROST, G., RUMPEL, D., "Network Restoration Expert System.", *Preprints of 1989 IFAC Symposium on Power Systems and Power Plant Control, Korea*, pp. 693 - 696.
- ✧ 125. LAING, W.D., METCALFE, M.J., "Computer-assisted Demand Forecasting for Power System Control.", *CEGB Research Report*, Jan. 1986.
- ✧ 126. LAING, W.D., SMITH, D.G.C., "A Comparison of Time Series Forecasting Methods for Predicting the CEGB Demand.", *9th. PSCC Portugal*, pp. 369 - 375.
- ✧ 127. LAJDA, P., REICHERT, K., "An Interactive Short-term Load Forecasting Program.", *7th. PSCC Lausanne*, pp. 553 - 557.
- 128. LATHAM, G.H., "Probability Approach to Electric Utility Load Forecasting.", *IEEE Trans. on PAS-87*, No. 2, Vol. 87, Feb. 1968, pp. 496 - 504.
- 129. LAUGHTON, M.A., TERJESON, N.J., "Medium and Long-term Energy Demand Forecasting: The Case for a Knowledge-based Approach.", *Symposium on expert systems application to power systems, Stockholm-Helsinki, Aug. 22-26, 1988*, pp. 7-10 - 7-17.

130. LAUTALA, P., VALLSUO, N., "A Hierarchical Expert System for Failure Diagnosis in Power Plants.", *Preprints of 1989 IFAC Symposium on Power Systems and Power Plant Control, Korea*, pp. 420 - 425.
- * 131. F., LI, "An Adaptive Approach for Short Term Demand Prediction Incorporating Weather Information", *MEMORANDUM, NGD Research in Confidence, NGD/L/TSP/0011/M89*.
- * 132. LIJESSEN, D.P., ROSING, J., "Adaptive Forecasting of Hourly Loads Based on Load Measurements and Weather Information.", *IEEE, Trans. on PAS-90*, No. 4, Vol. 90, July/Aug. 1971, pp. 1757 - 1767.
133. LIMAYE, D.R., "Implementation of Demand-Side Management Programs.", *Proceedings of IEEE*, No. 10, Vol. 73, Oct. 1985, pp. 1503 - 1513.
134. LIU, C.C, LEE, S.J., VENKATA, S.S., "An Expert System Operational Aid for Restoration and Loss Reduction of Distribution Systems.", *IEEE, Trans. on Power Systems*, No. 2, Vol. 3, May 1988, pp. 619 - 626.
- * 135. LIU, C.C, TOMSOVIC, K., "An Expert System Assisting Decision-making of Reactive Power/Voltage Control.", *Proceeding of Power Industry Computer Application Conference*, May 1987, pp. 242 - 248.
- * 136. LU, Q.C., GRADY, W.M., CRAWFORD, M.M., ANDERSON, G.M., "An Adaptive Nonlinear Predictor with Orthogonal Escalator Structure for Short-term Load Forecasting.", *IEEE Trans. on Power Systems*, No. 1, Vol. 4, Feb. 1989, pp. 158 - 164.
137. MARA, K., YAMASHIRO, S., YANAURA, Y., "Application of an Expert System to Decisions on Countermeasures Against Snow Accretion on Transmission Lines.", *IEEE Trans. on Power Systems*, No. 3, Vol. 3, Aug. 1988, pp. 1052 - 1058.
138. MARATHE, H., LIU, C.C., MA, T.K., "A Relational Representation of Complex Knowledge with Applications to Power System Problems.", *Symposium on expert systems application to power systems, Stockholm-Helsinki, Aug. 22-26, 1988*, pp. 2-4 - 2-9.

- * 139. MATTHEWMAN, P.D., "Further Investigations into the Method of Prediction of Load Demand Using the Spectral Expansion Technique.", *Departmental Control Group Report*, Sept. 1967.
- * 140. MATTHEWMAN, P.D, NICHOLSON, H, "Techniques for Load Prediction in the Electricity - Supply Industry.", *IEE Proceedings Part C*, IEE No. 10, Vol. 115, 1968, pp. 1451 - 1457.
- * 141. MATTHEWS, A., RUSSELL, L., CARPINELLA, C., "Weather-normalized Intermediate Term Capacity Forecasting: A Procedual Innovation.", *IEEE Trans. on Power Systems*, No. 3, Vol. 3, Aug. 1988, pp. 1291 - 1297.
- 142. MELAMED, A.M., MORZHIN, Y.I., TIMCHENKO, V.F., TSVETKOV, E.V., ZHARKIN, V.F., "Improvement of Electric Power System Load Forecasting and Operational Planning for Control Automation.", *Electrical Power and Energy Systems*, Vol. 11, No. 3, July 1989, pp. 218 - 222.
- 143. MIHELICIC, M., GUBINA, F., OGORELEC, A., "An Approach to Power Network Fault Location Diagnosis.", *Symposium on expert systems application to power systems, Stockholm-Helsinki, Aug. 22-26, 1988*, pp. 4-26 - 4-31.
- 144. MINAKAWA, T., TAGATA, K., "An Advanced Integrated System for Electric Energy Supply Planning.", *Preprints of 1989 IFAC Symposium on Power Systems and Power Plant Control, Korea*, pp. 330 - 335.
- 145. MIYAMOTO, E., KOIKE, T. "Adaptive Load Prediction by Orthogonal Polynomials.", *Electrical Engineering in Japan*, No. 4, Vol. 90, July-Aug. 1971, pp. 59 - 67.
- * 146. MOGHRAM, I., RAHMAN, S., "Analysis and Evaluation of Five Short-term Load Forecasting Techniques.", *IEEE Trans. on Power Systems*, No. 4, Vol. 4, Oct. 1989, pp. 1484 - 1491.
- * 147. MOKHTARI, S., SINGH, J., WOLLENBERG, B., "A Unit Commitment Expert System.", *IEEE Trans. on Power Systems*, No. 1, Vol. 3, Feb. 1988, pp. 272 - 277.
- * 148. MOMOH, J.A., "Expert System Based Power Flow Evaluation.", *Symposium on expert systems application to power systems, Stockholm-Helsinki, Aug. 22-26, 1988*, pp. 12-22 - 12-26.

- ✧ 149. MOTTER, J.W., MCGINLEY, J.P., "Validation of End-use Load Data from Direct Metering Projects.", *IEEE Computer Application in Power*, July 1988, pp. 33 – 36.
- 150. MOUTTER, S.P., BODGER, P.S., GOUGH, P.T., "Spectral Decomposition and Extrapolation of Variations in Electricity Loading.", *IEE Proceedings Part C*, IEE No. 5, Vol. 133, July, 1986, pp. 247 – 255.
- ✧ 151. MULLER, H., "An Approach to Very Short Term Load Forecasting by Exponential Smoothing with Trend Correction Based on Previous Day Comparison and Error Difference Smoothing.", *6th. PSCC Darmstadt*, pp. 417 – 425.
- ✧ 152. MULLER, H., "Classification of Daily Load Curves by Cluster Analysis.", *8th. PSCC Helsinki*, pp. 381 – 388.
- ✧ 153. MULLER, H. LAYR, P. "Very Short Term Load Forecasting – Description of an Efficient Method.", *7th. PSCC Lausanne*, pp. 495 – 499.
- ✧ 154. NASSAR, M.K., GRUBER, S., "Stochastic End-use Model for Forecasting Load Statistics.", *Electrical Power and Energy Systems*, Vol. 8, No. 3, July 1986, pp. 182 – 191.
- 155. NELSON, W.R., "Reactor: an Expert System for Diagnosis and Treatment of Nuclear Reactor Accidents.", *Proceedings of the AAAI 82, Pittsburgh*, pp. 296 – 301.
- 156. OATTS, M.L., ERWIN, S.R., HART, J.L., "Application of the REI Equivalent for Operation Planning Analysis of Interchange Schedules.", *IEEE Trans. on Power Systems*, No. 2, Vol. 5, May 1990, pp. 547 – 555.
- ✧ 157. OKADA, K., YOKOYAMA, R., SASAKI, H., "Knowledge-based System for Real-time Load Frequency Control in Multi-area Power System.", *Symposium on expert systems application to power systems, Stockholm-Helsinki, Aug. 22-26, 1988*, pp. 11-20 – 11-27.
- 158. PALAYANON, V., SINSAWAD, A., JURAMONGKORN, B., WILLIS, H.L., POWELL, R.W., TRAM, H.N., "Computerized Distribution Load Forecast for the City of Bangkok.", *IEEE Trans. on Power Systems*, No. 1, Vol. PWRS-2, Feb. 1987, pp. 218 – 225.

- ✧ 159. PARK, Y.M., LEE, H.J., "An Expert System for Fault Diagnosis in a Power System.", *Preprints of 1989 IFAC Symposium on Power Systems and Power Plant Control, Korea*, pp. 697 – 701.
- ✧ 160. PARK, Y.I., PARK, J.K., "An Expert System for Short Term Load Forecasting by Fuzzy Decision.", *Preprints of 1989 IFAC Symposium on Power Systems and Power Plant Control, Korea*, pp. 831 – 836.
- 161. PEHRSSON, T.B., "Power System Planning Using Expert System Technology.", *Symposium on expert systems application to power systems, Stockholm-Helsinki, Aug. 22-26, 1988*, pp. 16-14 – 16-17.
- ✧ 162. PIGGOTT, J.L., "Short-term Forecasting at British Gas.", *Comparative Models for Electrical Load Forecasting, John Wiley and Sons Ltd.*, 1985.
- ✧ 163. PÖYSTI, K., "Box-Jenkins Method in Short-term Forecasting of Grid Load in Finland.", *8th. PSCC Helsinki*, pp. 357 – 368.
- 164. PRICE, D.H.R., SHARP, J.A., "Investigation of the Impact of Changes in Demand Forecasting Method on the Financial Performance of an Electricity Supply Undertaking.", *Electrical Power and Energy Systems*, Vol. 7, No. 3, July 1985, pp. 131 – 137.
- 165. QUINTANA, A., GOMEZ, J., REPPEN, N.D., "Integration of an Adaptive Short Term Load Forecast Procedure into a New Energy Control Center.", *7th. PSCC Lausanne*, pp. 426 – 431.
- 166. RAHMAN, S., BABA, M., "Software Design and Evaluation of a Microcomputer-Based Automated Load Forecasting System.", *IEEE Trans. on Power Systems*, No. 2, Vol. 4, May 1989, pp. 782 – 788.
- ✧ 167. RAHMAN, S., BABA, M., "An Integrated Load Forecasting - Load Management Simulator: its Design and Performance.", *IEEE Trans. on Power Systems*, No. 1, Vol. 4, Feb. 1989, pp. 184 – 189.
- ✧ 168. RAHMAN, S. BHATNAGAR, R. "An Expert System Based Algorithm for Short Term Load Forecast.", *IEEE Trans. on Power Systems*, No. 2, Vol. 3, May 1988, pp. 392 – 399.

- * 169. RAJURKAR, K.P., NISSEN, J.L., "Data-Dependent Systems Approach to Short-Term Load Forecasting.", *IEEE Trans. on Systems, Man, and Cybernetics, SMC-15*, No. 4, Vol. 15, July/August 1985, pp. 332 - 336.
- * 170. RAMSAY, B., ZITOUNI, S., MOFFATT, A., MOYES, I. "An Expert System Interface for Optimal Power-flow Studies.", *Symposium on expert systems application to power systems, Stockholm-Helsinki, Aug. 22-26, 1988*, pp. 13-14 - 18.
- * 171. RAUCH-HINDIN, W.B., "Artificial Intelligence in Business, Science, and Industry Vol I - Fundamentals.", *Prentice-Hall*, 1986.
- * 172. RAUCH-HINDIN, W.B., "Artificial Intelligence in Business, Science, and Industry Vol II - Applications.", *Prentice-Hall*, 1985.
173. REED, J.H., BROADWATER, R.P., "Predicting Air Conditioner Load Curves from Energy Audit Data: A Comparison of Predicted and Actual Air Conditioning Data from the Athens Load Control Experiment.", *IEEE Trans. on Power Systems*, No. 2, Vol. 5, May 1990, pp. 359 - 365.
- * 174. REMIOR, M., AYUSO, J.L., "E.L.F.O.S. Expert System for Short-term Load Forecasting.", *Symposium on expert systems application to power systems, Stockholm-Helsinki, Aug. 22-26, 1988*, pp. 7-5 - 7-9.
- * 175. RIBEIRO, J.R., LANGE, F.J., "A New Aggregation Method for Determining Composite Load Characteristics.", *IEEE Trans. on PAS-101*, No. 8, Vol. 101, Aug. 1982, pp. 2869 - 2875.
176. ROBSON, N., "Cable Details and Consumer Type Details Held in Program Backing Store.", *The North Eastern Electricity Board Network Design Program DEBUT*, HV/LV Design, Planning Managers Section, Nov. 1984.
177. RUNNEL, J.E., WHYTE, M.D., "Evaluation of Demand-Side Management.", *Proceedings of IEEE*, No. 10, Vol. 73, Oct. 1985, pp. 1489 - 1495.
178. RYAN, N.E., POWERS, J.T., BRAITHWAIT, S.D., SMITH, B.A., "Generalising Direct Load Control Program Analysis: Implementation of the Duty Cycle

- Approach.”, *IEEE Trans. on Power Systems*, No. 1, Vol. 4, Feb. 1989, pp. 293 – 297.
- * 179. SAKAGUCHI, T., TANAKA, H., UENISHI, K., GOTOH, T., SEKINE, Y., “Prospects of Expert Systems in Power System Operation.”, *Electrical Power and Energy Systems*, No. 2, Vol. 10, April 1988, pp. 71 – 82.
180. SATOH, H., SERIZAWA, Y., “Fuzzy Decision-making on Electric Energy Strategy for Long-term Generation Expansion Planning.”, *Preprints of 1989 IFAC Symposium on Power Systems and Power Plant Control, Korea*, pp. 308 – 312.
- * 181. SCHICK, I.C., USORO, P.B., RUANE, M.F., HAUSMAN, J.A., “Residential End-use Load Shape Estimation from Whole-house Metered Data.”, *IEEE Trans. on Power Systems*, No. 3, Vol. 3, Aug. 1988, pp. 986 – 991.
- * 182. SCHICK, I.C., USORO, P.B., RUANE, M.F., SCHWEPPE, F.C., “Modelling and Weather Normalisation of Whole-House Metered Data for Residential End-use Load Shape Estimation.”, *IEEE Trans. on Power Systems*, No. 1, Vol. 3, Feb. 1988, pp. 213 – 219.
183. SCHULTE, R.P., SHEBLE, G.B., LARSEN, S.L., WRUBEL, J.N., “Artificial Intelligence Solution to Power System Operating Problems.”, *IEEE Trans. on Power Systems*, No. 4, Vol. PWRS-2, Nov. 1987, pp. 920 – 926.
184. SCHWEPPE, F.C., DARYANIAN, B., TABORS, R.D., “Algorithms for a Spot Price Responding Residential Load Controller.”, *IEEE Trans. on Power Systems*, No. 2, Vol. 4, May 1989, pp. 507 – 516.
185. SEKINE, Y., “Application of AI Techniques to Power System.”, *Symposium on expert systems application to power systems, Stockholm-Helsinki, Aug. 22-26, 1988*, pp. 0-1 – 0-4.
186. SHACKSHAFT, G., “General Purpose Model of Power System Loads.”, *IEE Proceedings Part B*, IEE No. 8, Vol. 124, Aug. 1977, pp. 715 – 723.

- * 187. SHAH, S., SHAHIDEHPOUR, S.M., "A Heuristic Approach to Load Shedding Scheme.", *IEEE Trans. on Power Systems*, No. 4, Vol. 4, Oct. 1989, pp. 1421 - 1429.
188. SHARMA, K.L., MAHALANABIS, A.K., "Harmonic Analysis via Kalman Filtering Technique.", *Proceedings of IEEE*, No. 3, Vol. 61, March 1973, pp. 391 - 392.
- * 189. SHARMA, K.L., MAHALANABIS, A.K., "Recursive Short-term Load-forecasting Algorithm.", *IEE Proceedings Part C*, IEE No. 1, Vol. 121, Jan. 1974, pp. 59 - 62.
190. SHIRAI, G., TAMURA, Y., KERMANSHAHI, B.S., YOKOYAMA, R., "Expert System for Power System Stabilisation Based upon the Second Lyapunov Function.", *Symposium on expert systems application to power systems, Stockholm-Helsinki, Aug. 22-26, 1988*, pp. 5-9 - 5-15.
- * 191. SHUAIB, A.N., ELAMIN, I.M., "Dynamic Data System Modelling of Electrical Power Demand.", *Electrical Power and Energy Systems*, No. 3. Vol. 9, Oct. 1987, pp. 250 - 254.
- * 192. SINGH, A., EMMANUAL, P., KALRA, P.K., "Point of View for Development of Knowledge Based System for Load Forecasting.", *Symposium on expert systems application to power systems, Stockholm-Helsinki, Aug. 22-26, 1988*, pp. 7-1 - 7-4.
- * 193. SKINNER, N.H., "Load Research and its Application to Electricity Demand Forecasting.", *The Statistician*, 33, 1984, pp. 65 - 73.
194. SMITH, A., MCRAE, M.R., TABAKIN, E.L., "Issues in Forecasting Demand-Side Management Program Impacts.", *Proceedings of IEEE*, No. 10, Vol. 73, Oct. 1985, pp. 1497 - 1503.
- * 195. SMITH, D.G.C., "Short Term Load Demand Prediction Using a Univariate Box-Jenkins Forecasting Method.", *MEMORANDUM, CEGB Research in Confidence, TPRD/L/CI389/M86*. 1986.
- * 196. SMITH, D.G.C., "Demand Forecasting over Special Periods Using a Modified Box-Jenkins Method", *CEGB Research in Confidence, TPRD/L/ECS162/M87*, 1987.

- * 197. SMITH, D.G.C., "Suggested Algorithmic Structures for a Multivariate On-line Demand Prediction Facility.", *CEGB Research in Confidence, TPRD/L/ECS0354/M88*, May 1988.
198. SMOLLECK, H.A., KIM, K.C., "An Interactive Distribution Load Forecasting Methodology for Minicomputer Use Based upon a Markov - Type Process.", *IEEE Trans. on Power Systems*, No. 1, Vol. 3, Feb. 1988, pp. 52 - 58.
199. SOBAJIC, D.J., PAO, Y.H., "An Artificial Intelligence System for Power System Contingency Screening.", *IEEE Trans. on Power Systems*, No. 2, Vol. 3, May 1988, pp. 647 - 653.
- * 200. SRINIVASAN, N., PRONOVOST, R. "Short Term Load Forecasting Using Multiple Correlation Models.", *IEEE Trans. on PAS-94*, No. 5, Vol. 94, Sept./Oct. 1975, pp. 1854 - 1858.
201. STALDER, M., NIEBUR, D., PALMIERE, L., GERMOND, A.J., "A Rule-based System for Substation Monitoring: The Switching Operations.", *Symposium on expert systems application to power systems, Stockholm-Helsinki, Aug.22-26, 1988*, pp. 6-1 - 6-8.
202. STANTON, K.N., "Forecasting by Probability Methods.", *IEEE Trans. on PAS-90*, No. 3, Vol. 90, May/June 1971, pp. 1183 - 1189.
203. STANTON, K.N., "Medium-range, Weekly and Seasonal Peak Demand Forecasting by Probability Methods.", *IEEE Trans. on PAS-90*, No. 3, Vol. 90, May/June 1971, pp. 1183 - 1189.
204. STANTON, K.N., GUPTA, P.C., "Forecasting Annual or Seasonal Peak Demand in Electric Utility Systems.", *IEEE Trans. on PAS-89*, No. 5/6, Vol. 89, May/June 1970, pp. 951 - 959.
205. STEPHENS, R.E., "Load Control Demand Reduction Estimation.", *IEEE Trans. on Power Systems*, No. 1, Vol. 3, Feb. 1988, pp. 59 - 66.
- * 206. STERLING, M.J.H., "Power System Control.", *IEE, Peter Peregrinus Ltd.*, London, 1978, Isbn. 0 86341 085 5.

- * 207. STERLING, M.J.H., ANTELIFFE, D.J., "A Technique for the Prediction of Water Demand from Past Consumption Data only.", *Inst. of Water Engineers*, No. 8, Vol. 28, 1974, pp. 413 - 420.
- * 208. STERLING, M.J.H., BARGIELA, A., "The Enhancement of Time Series Modelling Techniques for Adaptive Forecasting.", *Department of Engineering*, University of Durham.
209. STRICHLER, G.F., NOELL, S.K., "Residential Air Conditioner Cycling: A Case Study.", *IEEE Trans. on Power Systems*, No. 1, Vol. 3, Feb. 1988, pp. 207 - 212.
210. TAKEYASU, I., FUKUTA, T., KUNUGI, M., SHINOHARA, J., NAGATA, J., "An Expert System for Fault Analysis and Restoration of Trunk Line Power Systems.", *Symposium on expert systems application to power systems, Stockholm-Helsinki, Aug. 22-26, 1988*, pp. 8-24 - 8-31.
211. TALUKDAR, S.N., CARDOZO, E., PERRY, T., "The Operator's Assistant: An Intelligent, Expandable Program for Power System Trouble Analysis.", *IEEE Trans. on Power Systems, PWRS-1*, No. 3, Vol. 1, Aug. 1986, pp. 182 - 187.
212. TANGEN, G., HUSOM, M., "A Knowledge Based Tool for Analysing Power System Behaviour.", *Symposium on expert systems application to power systems, Stockholm-Helsinki, Aug. 22-26, 1988*, pp. 12-27 - 12-34.
213. TAYLOR, T., LUBKEMAN, D., "Applications of Knowledge-based Programming to Power Engineering Problems.", *IEEE Trans. on Power Systems*, No. 1, Vol. 4, Feb. 1989, pp. 345 - 352.
214. TEIXEIRA, M.J., PINTO, H.J.C.P., PEREIRA, M.V.F., MCCOY, M.F., "Developing Concurrent Processing Applications to Power System Planning and Operations.", *IEEE Trans. on Power Systems*, No. 2, Vol. 5, May 1990, pp. 659 - 664.
215. TESCH, D.B., YU, D.C., FU, L.M., VAIRAVAN, K., "A Knowledge-based Alarm Processor for an Energy Management System.", *IEEE Trans. on Power Systems*, No. 1, Vol. 5, Feb. 1990, pp. 268 - 275.

- ✧ 216. THE ELECTRICITY COUNCIL LOAD RESEARCH, "Industrial and Commercial Customers with Demand of 1 MW and over, Standard Industrial Classification (1980) Analysis - 1987/88.", *Corporate Development Department, LR Note 1/89*, April 1989.
- 217. THE ELECTRICITY COUNCIL LOAD RESEARCH, "Load Characteristics of Commercial Customers in 1987/88, Analysis by Annual Load Factor Ranges within Selected Maximum Demand Ranges.", *Corporate Development Department, LR 645*, June 1989.
- ✧ 218. THE ELECTRICITY COUNCIL LOAD RESEARCH, "Load Characteristics of Commercial Customers in 1987/88, Analysis by Type of Premise and by Annual Consumption Ranges.", *Corporate Development Department, LR 643*, April 1989.
- 219. THE ELECTRICITY COUNCIL LOAD RESEARCH, "Load Characteristics of Domestic Economy 7 Customers in 1986/87.", *Corporate Development Department, LR 620*, Aug. 1988.
- 220. THE ELECTRICITY COUNCIL LOAD RESEARCH, "Load Characteristics of Domestic Economy 7 Customers in 1987/88.", *Corporate Development Department, LR 620*, Aug. 1988.
- ✧ 221. THE ELECTRICITY COUNCIL LOAD RESEARCH, "Load Characteristics of Industrial Customers in 1987/88, Analysis by Annual Maximum Demand and Consumption Ranges.", *Corporate Development Department, LR 651*, June 1989.
- 222. THE ELECTRICITY COUNCIL LOAD RESEARCH, "Load Characteristics of Industrial Customers in 1987/88, Analysis by Trade Group.", *Corporate Development Department, LR 654*, Oct. 1989.
- ✧ 223. THE ELECTRICITY COUNCIL LOAD RESEARCH, "Load Characteristics of Unrestricted Supplies to Domestic Customers 1987/88, Supplementary Analysis by Appliance Usage.", *Corporate Development Department, LR 647*, April 1989.
- ✧ 224. THOMPSON, R.P., "Weather Sensitive Electric Demand and Energy Analysis on a Large Geographically Diverse Power System - Application

- to Short Term Hourly Electric Demand Forecasting.”, *IEEE Trans. on PAS-95*, No. 1, Vol. 95, Jan/Feb. 1976, pp. 385 – 393.
225. TOMSOVIC, K., “Evaluating Rule-based Systems.”, *Symposium on expert systems application to power systems, Stockholm-Helsinki, Aug. 22-26, 1988*, pp. 2-1 – 2-3.
- * 226. TORRES, G.L., VALIQUETTE, B., MUKHEDKAR, D., “Short-term Feeder Load Forecasting: an Expert System Using Fuzzy Logic.”, *Preprints of 1989 IFAC Symposium on Power Systems and Power Plant Control, Korea*, pp. 825 – 830.
227. TOYAMA, M., YAMADA, K., “Daily Load Prediction on the Basis of Farmer’s Method.”, *Electr. Engineering. in Japan*, No. 7, Vol. 87, July 1967, pp. 50 – 58.
- * 228. TOYODA, J., CHEN, M., INOUE, Y., “An Application of State Estimation to Short-Term Load Forecasting, Part I: Forecasting Modelling.”, *IEEE Trans. on PAS-89*, No. 7, Vol. 89, Sept./Oct. 1970, pp. 1678 – 1688.
229. TRACE, A., YOKOE, J.M., “Residential Cool Storage: Peak Load Reduction Alternatives.”, *IEEE Trans. on Power Systems*, No. 3, Vol. 3, Aug. 1988, pp. 837 – 843.
230. TRAM, H.N., WILLIS, H.L., NORTHCOTE-GREEN, J.E.D., BROOKS, C.L., “Load Forecasting Data and Data Base Development for Distribution Planning.”, *IEEE Trans. on PAS-102*, No. 11, Vol. 102, Nov. 1983, pp. 3660 – 3666.
- * 231. TSOI, A.C., KOBE, M.U., “Load Forecasting in a Power System from a Supply Authority Point of View.”, *Electric Power Systems Research*, No. 1, Vol. 6, Jan. 1983, pp. 147 – 159.
232. UNDRILL, J.M., KOSTYNIK, T.E., “Advanced Power System Fault Analysis Method.”, *IEEE Trans. on PAS-94*, No. 6, Vol. 94, Nov./Dec. 1975, pp. 2141 – 2150.
233. VÄHÄKYLÄ, P., HAKONEN, E., LÉMAN, P., “Short-term Forecasting of Grid Load in Finland.”, *6th. PSCC Darmstadt*, pp. 393 – 400.

- ✧ 234. VEMURI, S., HUANG, W.L., NELSON, D.J., "On-line Algorithms for Forecasting Hourly Loads of an Electric Utility.", *IEEE Trans. on PAS-100*, No. 8, Vol. 100, Aug. 1981, pp. 3775 - 3784.
- 235. VENTURI, R.C., FUSCO, B.M., "A Medium-term Forecasting Model for Electric Energy Demand.", *6th. PSCC Darmstadt*, pp. 582 - 587.
- 236. VLAHOVIĆ, V.M., VUJOSEVIĆ, I.M., "Long-term Forecasting: a Critical Review of Direct-trend Extrapolation Methods.", *Electrical Power and Energy Systems*, No. 1, Vol. 9, Jan. 1987, pp. 2 - 8.
- 237. VORBACH, A., SCHWINGSHANDL, H., RUMPEL, D., BROCKMANN, M., "Power System Restorations - Methods and Model-Simulations.", *IFAC Brussels, 5-8 Sept. 1988*, pp. 9.4.1 - 9.4.5.
- 238. WAGNER, W.R., KEYHANI, A., HAO, S., WONG, T.C., "A Rule-based Approach to Decentralized Voltage Control.", *IEEE Trans. on Power Systems*, No. 2, Vol. 5, May 1990, pp. 643 - 651.
- ✧ 239. WATERMAN, D.A., "A Guide to Expert Systems.", *Addison-Wesley Publishing Company*, 1985.
- ✧ 240. WEHENKEL, L., CUTSEM, T.V., RIBBENS-PAVELLA, M., "An Artificial Intelligence Framework for On-line Transient Stability Assessment of Power Systems.", *IEEE Trans. on Power Systems*, No. 2, Vol. 4, May 1989, pp. 789 - 800.
- 241. WILLIS, H.L., "Load Forecasting for Distribution Planning: Error and Impact on Design.", *IEEE Trans. on Power Systems*, March 1983, pp. 675.
- 242. WILLIS, H.L., BROOKS, C.L., "An Interactive End-use Electric Load Model for Microcomputer Implementation.", *IEEE Trans. on PAS-102*, No. 11, Vol. 102, Nov. 1983, pp. 3693 - 3700.
- 243. WILLIS, H.L., NORTHCOTE-GREEN, J.E.D., "Comparison Tests of Fourteen Distribution Load Forecasting Methods.", *IEEE Trans. on PAS-103*, No. 6, Vol. 103, June 1984, pp. 1190 - 1197.

- ✧ 244. WILLIS, H. L., NORTHCOTE-GREEN, J.E.D., POWELL, R.W., "Computerised Small Area Load Forecasting.", *7th. PSCC Lausanne*, pp. 545 – 552.
- 245. WILLIS, H.L., PARKS, T.W., "Fast Algorithms for Small Area Electric Load Forecasting.", *IEEE Trans. on PAS-102*, No. 10, Vol. 102, Oct. 1983, pp. 3425 – 3432.
- 246. WILLIS, H.L., POWELL, R.W., TRAM, H.N., "Long-range Distribution Planning with Load Forecast Uncertainty.", *IEEE Trans. on Power Systems*, No. 3, Vol. PWRS-2, Aug. 1987, pp. 684 – 691.
- 247. WILLIS, H.L., SCHAUER, A.E., NORTHCOTE-GREEN, J.E.D., VISMOR, T.D., "Forecasting Distribution System Loads Using Curve Shape Clustering.", *IEEE Trans. on PAS-102*, No. 4, Vol. 102, April 1983, pp. 893 – 901.
- 248. WILLIS, H.L., TRAM, H.N., "A Cluster Based V.A.I. Method for Distribution Load Forecasting.", *IEEE Trans. on PAS-102*, No. 8, Vol. 102, Aug. 1983, pp. 2677 – 2684.
- ✧ 249. WILLIS, H.L., TRAM, H.N., POWELL, R.W., "A Computerized, Cluster Based Method of Building Representative Models of Distribution Systems.", *IEEE Trans. on PAS-104*, No. 12, Vol. 104, Dec. 1985, pp. 3469 – 3474.
- 250. WILLIS, H.L., VISMOR, T.D., POWELL, R.W., "Some Aspects of Sampling Load Curve Data on Distribution Systems.", *IEEE Trans. on PAS-104*, No. 11, Vol. 104, Nov. 1985, pp. 3221 – 3228.
- ✧ 251. WOLLENBERG, B. F., SAKAGUCHI, T., "Artificial Intelligence in Power System Operations.", *Proceedings of the IEEE*, No. 12, Vol. 75, Dec. 1987, pp. 1678 – 1685.
- ✧ 252. WOLLENBERG, B.F., "Feasibility Study for an Energy Management System Intelligent Alarm Processor.", *IEEE Trans. on Power Systems, PWRS-1*, No. 2, Vol. 1, May 1986, pp. 241 – 247.
- 253. WONG, K.P., CHEUNG, H.N., "Expert System for Protection Current Transformer Design Specification Preparation.", *IEE Proceedings Part C, IEE* No. 6, Vol. 136, Nov. 1989, pp. 391 – 400.

- ✧ 254. WONG, K.P., CHEUNG, H.N., "Thermal Generator Scheduling Algorithm Based on Heuristic-guided Depth-first Search.", *IEE Proceedings Part C*, IEE No. 1, Vol. 137, Jan. 1990, pp. 33 - 43.
- 255. WOODS, W.A., "Important Issues in Knowledge Representation.", *Proceeding of the IEEE*, No. 10, Vol. 74, Oct. 1986, pp. 1322 - 1334.
- ✧ 256. XU, L.Z., "Application of the Innovation Method of Random Series in Power System Short-term Load Forecasting.", *7th. PSCC Lausanne*, pp. 500 - 507.
- 257. XUE, Y.S., "Preliminary Design of a Hybrid System for Transient Security of Power Systems.", *Symposium on expert systems application to power systems, Stockholm-Helsinki, Aug. 22-26, 1988*, pp. 5 - 16 - 5 - 21.
- ✧ 258. ZHANG, X.R., YU, Y.H., "On-line Decision-making of Reactive Power / Voltage Optimal Control Using Artificial Intelligence Approach.", *Preprints of 1989 IFAC Symposium on Power Systems and Power Plant Control, Korea*, pp. 116 - 119.
- 259. ZHANG, Z.Z., HOPE, G.S., MALIK, O.P., "Expert Systems in Electric Power Systems - A Bibliographical Survey.", *IEEE Trans. on Power Systems*, No. 4, Vol. 4, Oct. 1989, pp. 1355 - 1362.

* : indicator of reference.

APPENDIX 1

CALCULATION OF AUTOCORRELATION FUNCTION

For a times series $z(t), t = 0, 1, 2, \dots, n$, its autocovariance at lag k is defined as:

$$\begin{aligned}\gamma_k &= \text{cov}[z_t, z_{t+k}] \\ &= E[(z_t - \mu)(z_{t+k} - \mu)]\end{aligned}$$

where μ is the mean of the process:

$$\mu = E[(z_t)]$$

The autocorrelation function at lag k is

$$\begin{aligned}\rho_k &= \frac{E[(z_t - \mu)(z_{t+k} - \mu)]}{\sqrt{E[(z_t - \mu)^2]E[(z_{t+k} - \mu)^2]}} \\ &= \frac{E[(z_t - \mu)(z_{t+k} - \mu)]}{\sigma_z^2}\end{aligned}$$

where σ_z^2 is the variance of the process. For a stationary process, $\sigma_z^2 = \gamma_0$.

Thus, the autocorrelation function at lag k is

$$\rho_k = \frac{\gamma_k}{\gamma_0}$$

which implies that $\rho_0 = 1.0$.

The above is the theoretical autocorrelation function. A number of estimates of the autocorrelation function have been suggested by statisticians. But the most satisfactory estimate of the k th lag autocorrelation function ρ_k is:

$$r_k = \frac{c_k}{c_0}$$

where:

$$c_k = \frac{1}{N} \sum_{t=1}^{N-k} (z_t - \bar{z})(z_{t+k} - \bar{z}), k = 0, 1, 2, \dots, K$$

is the estimate of the autocovariance γ_k , and \bar{z} is the mean of the time series:

$$\bar{z} = \frac{1}{N} \sum_{t=1}^N z_t$$

The autocorrelation function reveals how the correlation between any two values of the series changes as their separation changes. Therefore, it can be used to detect periodicals in the time series.

APPENDIX 2

LOAD FORECASTING PACKAGE

The overall load forecasting package consists of two parts: an ARIMA (auto-regressive integrated moving average) model and a knowledge based system. The whole prediction package is shown in the figure.

There are four components in the package: input, predictor, comparison and updating.

Input:

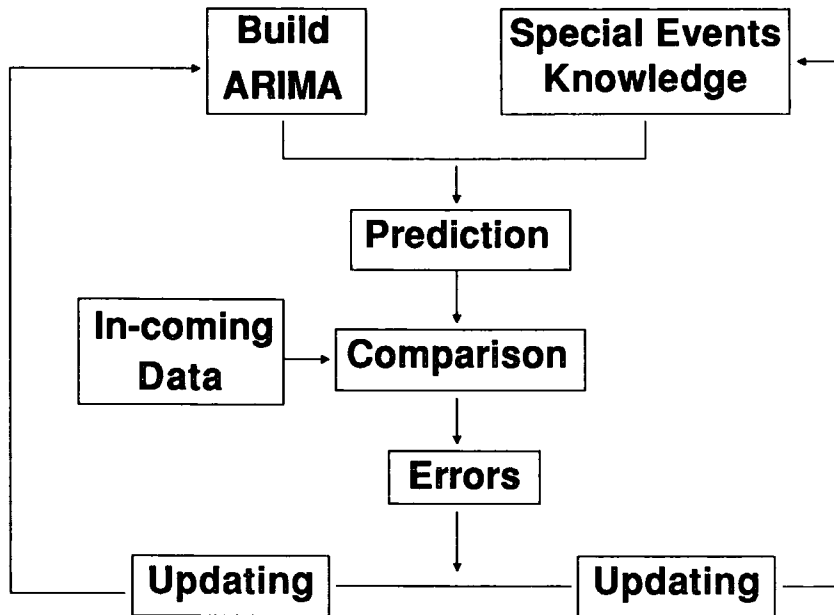
input the time and date to be forecast by users.

Predictor:

There are two parts in the predictor:

One is an ARIMA model which is used to predict normal weekday loads and weekend loads (including weather influence for weekend load prediction); and another one is the knowledge based system used to predict loads of special events.

When the ARIMA model is called, historical data are required to pass to the programme written in FORTRAN 77 in order to estimate the paramaters. The knowledge based system is written in POP-11.



Load Forecasting Systems

Comparison:

compare the forecasting results with the in-coming actual data.

Updating:

If the prediction is based on the ARIMA model, then the model parameters are updated; If the special event knowledge gives the prediction, then the knowledge is updated.

The following procedure illustrates the above package, which can predict loads of any day in 1985 (while some loads of 1983 and 1984 are stored in database). If it is a holiday, 24 hours of prediction from the midnight is performed. For further specific time with specific lead time, the user is required to input data. In the procedure, plist: prediction load in MW; act: actual data in MW; e_list: error list in %; rmserr: r.m.s. error of the prediction.

```

define prediction( ) → plist → act → e_list → rmserr;
vars rms_error,niter,rmserr,hol_date,l1,lrest,inf,yin,yini;
vars known,knownlist,partknownlist,unknownlist,wea_database;
vars tues_day1,tues_day2,lrest1,tues_load1,tues_load2,lrest3;
;;; variable declaration.
;;; request user to input date:
'input the date (day month year)'=>
[ ] → hol_date;
for s from 1 to 3 do
input_item( ) → item;
[^^hol_date ^item] → hol_date;
endfor;
;;; search through data base to find whether the date is a holiday.
find_public_day_type(hol_date) → special_day;
if special_day(2)="holiday" then
;;; if it is a holiday, call the procedure to predict.
pred_hol(hol_date,special_day) → plist → act → e_list → rmserr;
lb:
;;; request the user whether it is necessary to predict with lead
;;; time (<24 hours).
'Do you like to predict the load at t with lead time h?("y",or "n")...'=>
input_item( ) → yin;
if yin="y" then
;;; if yes, input the time.
input_time( ) → t → h;
;;; based on prediction of "pred_hol", correct older prediction
;;; error to new prediction, to output p: prediction value;
;;; a: actual value; e: error in %;
hol_t_h(plist,l1,act,t,h) → p → a → e;
elseif yin="n" then
;;; do nothing;
else
;;; if no input, keep on requesting.
goto lb;
endif;
goto Lend;    ;;; to exit.
else
;;; if not a holiday, to see whether is a Monday following the Monday
;;; Bank Holiday? e.g., the previous Monday is a holiday?
day_ndays_follow(hol_date,-7) → ref_day;
find_public_day_type(ref_day) → special_day;
if special_day(2)="holiday" then
'The day of last week is: '=> special_day=>
day_ndays_follow(ref_day,-6) → tues_day1;
day_ndays_follow(ref_day,1) → tues_day2;
day_ndays_follow(hol_date,-1) → last_day;
day_ndays_follow(hol_date,-41) → first_day;
if present ([== ^first_day ?l1 ??lrest1 [^^tues_day1 ==]
?tues_load1 ??lrest2 [^^ref_day ==] ?hol_l [^^tues_day2 ==]
?tues_load2 ??lrest3 [^^hol_date ??inf] ?l2 ==]) then
{^first_day ^l1 ^^lrest1 [^^tues_day1]
^tues_load1 ^^lrest2 [^^ref_day] ^tues_load2
[^^tues_day2] ^tues_load1 ^^lrest3} → knownlist;
;;; is yes, replace the Monday Bank Holiday loads,
;;; form historical loads and call the ARIMA.
goto la;

```

```

else
  'no proper past data for prediction...'=>
  goto Lend;   ;; to exit.
endif;
else
  ;; to find whether the day is around time change-overs.
  hol_date(3) → year;
  hol_date(2) → month;
  if month ≥ 10 and present ((= = bst_gmt [??day ^year])) then
    [^^day ^year] → day1;
    day_ndays_follow(day1,1) → new_day;
    day_ndays_follow(hol_date,0) → hol_date;
    if new_day(4)=ref_day(4) then
      'the reference day of last week is around change-over:
      bst - gmt!'=>
    endif;
    if new_day(4)=hol_date(4) then
      ;; the day is around bst-gmt change-over.
      ;; to call the procedure prediction_chg.
      [bst_gmt] → c_type;
      [[posnorm 1.0 216 6] [const 1.0 216.1 287.9] [negnorm 1.0 288 3]]
      → light_old;
      4000 → s_share;
      prediction_chg(hol_date,c_type,s_share) → plist → act
      → e_list → rmserr → e_max;
      "n" → yini;
      goto Lend;
    endif;
  elseif month ≥ 3 and present ((= = gmt_bst [??day ^year])) then
    [^^day ^year] → day1;
    day_ndays_follow(day1,1) → new_day;
    day_ndays_follow(hol_date,0) → hol_date;
    if new_day(4)=ref_day(4) then
      'the reference day of last week is around change-over:
      gmt - bst!'=>
    endif;
    if new_day(4)=hol_date(4) then
      ;; the day is around gmt-bst change-over.
      ;; to call the procedure prediction_chg.
      [gmt_bst] → c_type;
      6 → n_fact;
      hol_date(3) → year;
      gmt_bst_fact(year,n_fact) → fact;
      [[posnorm 1.0 216 4] [const 1.0 216.1 287.9] [negnorm 1.0 288 3]] →
light_old;
      4000 → s_share;
      prediction_chg(hol_date,c_type,s_share) → plist → act
      → e_list → rmserr → e_max;
      "n" → yini;
      goto Lend;
    endif;
  endif;
endif;
endif;
endif;
  ;; else it is a normal day (no time change overs, no holidays, etc.)
  ;; to form historical load, calling the ARIMA.

```

```

;;; the ARIMA model requires 6 weeks of data to estimate parameters.
'Today is:'=> find_public_day_type(hol_date)=>
day_ndays_follow(hol_date,-1) → last_day;
day_ndays_follow(hol_date,-41) → first_day;
if present ([== ^first_day ?l1 ??lrest [^^hol_date ??inf] ?l2 ==]) then
  {^first_day ^l1 ^^lrest} → knownlist;
  ;;; to form historical data used in the ARIMA parameter estimation.
else
  'no proper past data for prediction...'=>
  goto Lend;
endif;
la:
'Do you like to predict the load at t with lead time h?("y",or "n")...'=>
input_item( ) → yini;
if yini="y" then
  input_time( ) → t → h;
  allbutlast((length(l2)-t-h),l2) → temp;    ;;; only <49.
  allbutfirst(t,temp) → temp;
  {^hol_date ^temp} → unknownlist;
  h+1 → mpred;
  allbutlast((length(l2)-t),l2) → known;
  {^hol_date ^known} → partknownlist;
elseif yini="n" then
  {^hol_date ^l2} → unknownlist;
  49 → mpred;
  {[ ] [ ]} → partknownlist;
else
  goto la;
endif;
{^^knownlist ^^partknownlist} → knownlist;
data_past(knownlist,unknownlist) → past;
length(past) → mpast;
pred_call_arima(past,mpast,mpred) → pred → rmserr → niter;
allbutlast(1,rmserr) → rms_error;
if yini="y" then
  pred(mpred-1) → p;
  unknownlist(2)(mpred-1) → a;
  rms_error(mpred-1) → e;
else
  ;;; to calculate the errors.
  [ ] → plist;
  [ ] → act;
  [ ] → e_list;
  0 → rmserr;
  for i from 1 to mpred-1 do
    pred(i) → p;
    l2(i) → a;
    [^^act ^a] → act;
    [^^plist ^p] → plist;
    realof((p-a)/a)*100 → e;
    e*e + rmserr → rmserr;
    [^^e_list ^e] → e_list;
  endfor;
  sqrt(realof(rmserr/(mpred-1))) → rmserr;
endif;
Lend:

```

```

if yini="n" then
  'prediction results? (y,n)'==>
  input_item( ) → t;
  if t="y" then
nn:
  ;; send results to user.
  'predict load is: (p)'==>
  'actual load is: (a)'==>
  'the error (%): (err)'==>
  'RMS error (%): (rms)'==>
  'no: (n)'==>
  input_item( ) → t1;
  if t1="p" then
    plist==>
  elseif t1="a" then
    act==>
  elseif t1="err" then
    e_list==>
  elseif t1="rms" then
    rmserr==>
  endif;
  if t1/="n" then
    goto nn;
  endif;
endif;
elseif yini="y" then
  'prediction results? (y,n)'==>
  input_item( ) → t;
  if t="y" then
    'predict load is:'==> p==>
    'actual load is:'==> a==>
    'the error in per cent is:'==> e==>
  endif;
endif;
enddefine;

```

APPENDIX 3

SOME POP-11 PROGRAMMES

Listed below are some procedures used in load prediction of holidays, load around time change-overs, and the procedures to fit the overall load by individual components. In the POP-11, the sentence beginning with “;;;” is a comment.

1) Procedures for predicting holiday loads

After it is found that the “hol_date” is a “holiday” day-type (the procedure has been listed in the main chapter 6), the type of holiday is the head of “special_day”, the following procedure is called to conduct load prediction and calculate its errors.

```
define pred_hol(hol_date,special_day) → plist → act → e_list → rmserr;
  vars hol_date,plist,act,e_list,rmserr,yin;
  vars special_day,database_83,database_84;
  if special_day(2)="holiday" then
    ;;; if the date is a holiday.
    if member(special_day(1),[christmas_day boxing_day new_years_day]) then
      'It is a holiday:'=> special_day(1)==>
      ;;; sending message to user, if the holiday is a special holiday.
      ;;; (not Monday Bank Holiday).
      'only refer to holiday load of last year (y,n)?'=>
      input_item( ) → yin;
      if yin="y" then
        1 → nyears;
      else
        'how many (2)?'=>
        input_item( ) → nyears;
      endif;
      ;;; request for historical data (number of years) for references.
      pred_xmas(hol_date,nyears) → plist → act;
      ;;; call the procedure to predict and find its actual load.
    elseif member(special_day(1),[good_friday]) then
      'It is a holiday:'=> special_day(1)==>
      ;;; sending message to user, if the holiday is a Good_Friday
```

```

;;; (not Monday Bank Holiday).
'only refer to holiday load of last year (y,n)?'=>
input_item( ) → yin;
if yin="y" then
  1 → nyears;
else
  'how many (2)?'=>
  input_item( ) → nyears;
endif;
;;; request for historical data for references.
'weather effect included (y,n)?'=>
;;; ask whether weather effects (Max. temperature only) included.
input_item( ) → wea;
20 → n1; 36 → n2;
pred_hol_gf(hol_date,nyears,wea,n1,n2) → plist → act;
;;; call the procedure to predict Good Friday load.
else
  'It is a Monday Holiday:'=> special_day(1)=>
  ;;; sending message to user.
  'weather effect included (y,n)?'=>
  input_item( ) → yin;
  if yin="y" then
    20 → n1; 36 → n2;
    pred_hol_cor.t(hol_date,n1,n2) → plist → act;
    ;;; to predict holiday loads with weather effects considered.
    ;;; details listed below.
  else
    pro_hol(hol_date) → database_83 → database_84
    → act → sat_85 → sun_85;
    ;;; to find the appropriate reference load and best coefficients for
    ;;; Saturday and Sunday loads. Details listed below.
    post_hol(database_83,database_84,sat_85,sun_85) → plist;
    ;;; perform prediction. details listed below.
  endif;
endif;
0 → rmserr;
[ ] → e_list;
for i from 1 to length(act) do
  realof((plist(i)-act(i))/act(i))*100 → e;
  e*e+rmserr → rmserr;
  [^^e_list ^e] → e_list;
endfor;
sqrt(realof(rmserr/length(act))) → rmserr;
;;; calculating the rms error: rmserr.
endif;
enddefine;

```

The following procedure is to find the best coefficients for the change trend from the Saturday and Sunday loads to the Monday Bank Holiday: sat_a, sun_a, which are used by post_hol.

```

define hol_coef(database_83,database_84) → sat_a → sun_a;
  vars database_83,database_84,sat_a,sun_a;
  vars ii,list1,list2,list_sat,list_sun,n_iter,sun_a,sat_a,sun_an,sat_an;
  vars fact_n,pre_load,act_load,error_pcmt,error_com;
  vars sum_error,jj,t,sum_com,sign_a;
  0.5 → sat_a;
  0.5 → sun_a;
  ;;; default values are 0.5.
  1 → ii;
  database_83(ii+1) → list1;
  database_84(ii+1) → list2;
  divi_list(list2,list1) → list_sat;
  database_83(ii+3) → list1;
  database_84(ii+3) → list2;
  divi_list(list2,list1) → list_sun;
  -1 → n_iter;
  0.5 → sat_an; 0.5 → sun_an;
  -1 → sign_a;
Ls:
  [%repeat 48 times 0 endrepeat%] → fact;
  1+n_iter → n_iter;
  multiply(list_sat,sat_an) → list;
  addup(list,fact) → fact_n;
  multiply(list_sun,sun_an) → list;
  addup(list,fact_n) → fact_n;
  times_list(fact_n,database_83(ii+5)) → pre_load;
  copylist(database_84(ii+5)) → act_load;
  divi_list(difference(pre_load,act_load),act_load) → error_pcmt;
  error_rms(error_pcmt) → sum_error;
  ;;; actually, it is rms of error.
  if n_iter=0 then
    sum_error → sum_com;
    error_max → error_com;
    sat_a+sign_a*0.01 → sat_an;
    sun_a-sign_a*0.01 → sun_an;
    goto Ls;
  elseif sum_error<sum_com then
    sum_error → sum_com;
    sat_an → sat_a;
    sun_an → sun_a;
    sat_a+sign_a*0.01 → sat_an;
    sun_a-sign_a*0.01 → sun_an;
    if sat_an>0.20 and sun_an<0.8 then
      goto Ls;
    endif;
  elseif n_iter=1 then
    -sign_a → sign_a;
    goto Ls;
  endif;
enddefine;

```

The following procedures can be used to predict loads for Christmas Day, New Year's Day, Boxing Day.

```

define pred_xmas(hol_date,nyears) → plist → xmas_load;
vars hol_date,nyears,plist,e_list,rmserr,special_day,a,e,i;
find_public_day_type(hol_date) → special_day;
if special_day(2)="holiday" then
  pred_spec_hol(hol_date,nyears) → plist;
  if present ([== [^^hol_date ??inf] ?xmas_load ==]) then
    else
      'no actual load found in the database.'==>
    endif;
  endif;
endif;

enddefine;

define pred_spec_hol(hol_date,nyears) → p_list;
vars hol_date,nyear,special_day,day_t,p_year,d,hol_d,hol_ref,p_year_1;
vars hol_n,inf,dat_r,f,xmas_load,ii,m_load;
find_public_day_type(hol_date) → special_day;
day_ndays_follow(hol_date,0) → day_t;
hol_date(3)-nyears → p_year;
if present ([active == [%special_day(1)% ??d ^p_year]]) then
  [^^d ^p_year] → hol_d;
  ;;; to find the date of the same holiday in historical data.
  day_ndays_follow(hol_d,0) → hol_ref;
endif;
hol_date(3)-nyears+1 → p_year_1;
if present ([active == [%special_day(1)% ??d ^p_year_1]]) then
  [^^d ^p_year_1] → hol_d;
  ;;; to find the date of the same holiday in historical data.
  day_ndays_follow(hol_d,0) → hol_n;
endif;
if present ([== [^^hol_ref ??inf] ?xmas_load ==]) then
  ;;; find the historical holiday loads.
  [^^hol_ref ^^inf] → dat_r;
  type_factor(special_day,hol_n,dat_r) → f;
  multiply(xmas_load,f) → p_list;
endif;
if nyears>1 then
  for ii from 1 to nyears-1 do
    hol_date(3)-nyears+ii → p_year_1;
    if present ([active == [%special_day(1)% ??d ^p_year_1]]) then
      [^^d ^p_year_1] → hol_d;
      day_ndays_follow(hol_d,0) → hol_ref;
    endif;
    hol_date(3)-nyears+ii+1 → p_year_1;
    if present ([active == [%special_day(1)% ??d ^p_year_1]]) then
      [^^d ^p_year_1] → hol_d;
      day_ndays_follow(hol_d,0) → hol_n;
    endif;
    if present ([== [^^hol_ref ??inf] ?xmas_load ==]) then
      [^^hol_ref ^^inf] → dat_r;
      type_factor(special_day,hol_n,dat_r) → f;
      addup(p_list,xmas_load) → m_load;
      multiply(m_load,0.5) → xmas_load;
      ;;; average of predictions from historical holiday loads.
      multiply(xmas_load,f) → p_list;
    endif;
  endfor;
endif;

```

```

    endif;
  endfor;
endif;
enddefine;

```

This procedure is used for predicting Monday Bank Holiday load (24 hours ahead), used by post_hol (pred_hol).

```

define pred_hol_p(database_84,sat_85,sun_85,sat_a,sun_a) → pred_load;
  vars database_84,sat_85,sun_85,sat_a,sun_a,pred_load;
  vars fact,ii,list1,list;
  [%repeat 48 times 0 endrepeat%] → fact;
  1 → ii;
  database_84(ii+1) → list1;
  ;;; Saturday load.
  divi_list(sat_85,list1) → list;
  multiply(list,sat_a) → list;
  addup(list,fact) → fact;
  database_84(ii+3) → list1;
  ;;; Sunday load.
  divi_list(sun_85,list1) → list;
  multiply(list,sun_a) → list;
  addup(list,fact) → fact;
  times_list(fact,database_84(ii+5)) → pred_load;
enddefine;

```

This is used in pred_hol. It is used to find the historical load data of the same day type as the current day.

```

define pro_hol(hol_date) → database_83 → database_84 → act →
sat_85 → sun_85;
  vars hol_date,special_day,d_sun_85,d_sat_85,sat_85,sun_85,act,p_year,day;
  vars p_hol,list,d_sun_84,d_sat_84,sat_84,sun_84,d_mon,mon_84,database_84;
  vars d_sun_83,d_sat_83,d_sat,d_sun,d_mon,mon_83,database_84;
  vars sat_83,sun_83,days,change_date,hol_date_ref;
  day_ndays_follow(hol_date,0) → hol_date;
  -1 → days;
  day_ndays_follow(hol_date,days) → d_sun_85;
  day_ndays_follow(hol_date,days-1) → d_sat_85;
  find_public_day_type(hol_date) → special_day;
  if present ((== ^d_sat_85 ?sat_85 ^d_sun_85 ?sun_85 == ^hol_date ?act ==))
  then
    ;;; find the weekend loads preceding the holiday in present year.

```

```

hol_date(3)-1 → p_year;
[ ] → llist;
if present ([active holidays = [%special_day(1)% ??day ^p_year]]) then
  ;; to look for the data of same holiday last year.
  [^^day ^p_year] → p_hol;
  if member(p_hol(2),[3 4]) then
    if present ([= = gmt_bst [??date ^p_year]]) then
      [^^date ^p_year] → change_date;
      day_ndays_follow(change_date,1) → change_date;
      change_date(4) → weekth;
      day_ndays_follow(p_hol,0) → hol_date_ref;
      if hol_date_ref(4)=weekth then
        'the reference day is around gmt - bst change-over!'=>
        ;; sending message to user if the holiday is
        ;; around time change-overs.
      endif;
    endif;
  endif;
  day_ndays_follow(p_hol,days) → d_sun_84;
  day_ndays_follow(p_hol,days-1) → d_sat_84;
  if present ([== [^^d_sat_84 ??d_sat] ?sat_84 [^^d_sun_84 ??d_sun]
?sun_84 == [^^p_hol ??d_mon] ?mon_84 ==]) then
    [[^^d_sat_84 ^^d_sat] ^sat_84 [^^d_sun_84 ^^d_sun] ^sun_84
^^p_hol ^^d_mon] ^mon_84] → database_84;
    [^mon_84 ^^llist] → llist;
    ;; to search for the reference load in previous year.
  endif;
endif;
hol_date(3)-2 → p_year;
if present ([active holidays = [%special_day(1)% ??day ^p_year]]) then
  [^^day ^p_year] → p_hol;
  day_ndays_follow(p_hol,days) → d_sun_83;
  day_ndays_follow(p_hol,days-1) → d_sat_83;
  if present ([== [^^d_sat_83 ??d_sat] ?sat_83 [^^d_sun_83 ??d_sun]
?sun_83 == [^^p_hol ??d_mon] ?mon_83 ==]) then
    [[^^d_sat_83 ^^d_sat] ^sat_83 [^^d_sun_83 ^^d_sun] ^sun_83 [^^p_hol
^^d_mon] ^mon_83] → database_83;
    [^mon_83 ^^llist] → llist;
    ;; to search for the reference load two years ago.
  endif;
else
  [ ] → database_83;
endif;
endif;
enddefine;

```

The following procedure is for prediction when appropriate historical loads are available, used in pred_hol:

```

define post_hol(database_83,database_84,sat_85,sun_85) → plist;
  vars hol_date,database_83,database_84;
  vars plist,sat_a,sun_a,i,t,h,e,item,sat_83,sun_83;
  hol_coef(database_83,database_84) → sat_a → sun_a;
  pred_hol_p(database_84,sat_85,sun_85,sat_a,sun_a) → plist;
enddefine;

```

The following one is for Monday Bank Holiday load prediction with weather effects included, used in pred_hol:

```

define pro_hol_cor_t(hol_date,n1,n2) → database_83 → database_84
→ act → sat_85 → sun_85;
  vars hol_date,special_day,d_sun_85,d_sat_85,sat_85,sun_85,act,p_year,day;
  vars d_sun_83,d_sat_83,d_sat,d_sun,d_mon,mon_83,database_84;
  vars p_hol,l1ist,d_sun_84,d_sat_84,sat_84,sun_84,d_mon;
  vars mon_84,database_84,change_date,t_ob1,t_ob2;
  day_ndays_follow(hol_date,-1) → d_sun_85;
  day_ndays_follow(hol_date,-2) → d_sat_85;
  ;;; to find the preceding weekend loads.
  find_public_day_type(hol_date) → special_day;
  if wea_database matches [== [^^hol_date ==] ?wea_inf2 ==] then
    ;;; to search through database to find the weather information.
    wea_inf2(1) → t_ob;
    ;;; temperature for forecast day.
    if present ([==[^^d_sat_85 ==] ?sat_85 [^^d_sun_85 ==]
?sun_85 == [^^hol_date ==] ?act ==]) then
      load_cor_t_hol(d_sat_85,n1,n2,t_ob) → sat_85;
      load_cor_t_hol(d_sun_85,n1,n2,t_ob) → sun_85;
      ;;; correct the preceding weekend loads by the temperature deviations.
      hol_date(3)-1 → p_year;
      [ ] → l1ist;
      if present ([active holidays = [%special_day(1)% ??day ^p_year]])
then
        [^^day ^p_year] → p_hol;
        ;;; date of the holiday in previous year.
        if member(p_hol(2),[3 4]) then
          if present ([= = gmt_bst [??date ^p_year]]) then
            [^^date ^ p_year] → change_date;
            day_ndays_follow(change_date,1) → change_date;
            change_date(4) → weekth;
            day_ndays_follow(p_hol(0) → hol_date_ref;
            endif;
          endif;
        if wea_database matches [== [^^p_hol ==] ?wea_inf2 ==] then
          ;;; to find the weather information of the holiday last year.
          wea_inf2(1) → t_ob1;
          day_ndays_follow(p_hol,-2) → d_sat_84;
          day_ndays_follow(p_hol,-1) → d_sun_84;
          load_cor_t_hol(d_sat_84,n1,n2,t_ob1) → sat_84;
          load_cor_t_hol(d_sun_84,n1,n2,t_ob1) → sun_84;

```

```

;;; correct the weekend loads by the holiday temperature.
if present ([== [^^p_hol ??inf] ?mon_84 ==]) then
  [^d_sat_84 ^sat_84 ^d_sun_84 ^sun_84
  ^p_hol ^mon_84] → database_84;
  [^mon_84 ^^llist] → llist;
  hol_date(3)-2 → p_year;
  if present ([active holidays = [%special_day(1)% ??day ^p_year]))
  then
    [^^day ^p_year] → p_hol;
    if wea_database matches [== [^^p_hol ==] ?wea_inf2 ==] then
      wea_inf2(1) → t_ob2;
      day_ndays.follow(p_hol,-1) → d_sun_83;
      day_ndays.follow(p_hol,-2) → d_sat_83;
      load_cor_t_hol(d_sat_83,n1,n2,t_ob2) → sat_83;
      load_cor_t_hol(d_sun_83,n1,n2,t_ob2) → sun_83;
      if present ([== [^^p_hol ??inf] ?mon_83 ==]) then
        [^d_sat_83 ^sat_83 ^d_sun_83 ^sun_83
        ^p_hol ^mon_83] → database_83;
        [^mon_83 ^^llist] → llist;
      endif;
    endif;
    ;;; doing the same for the reference loads two years ago.
  else
    [ ] → database_83;
  endif;
else
  'no weather data (holiday) for year:'==> p_year==>
endif;
else
  'no weather data (holiday) for year:'==> p_hol==>
endif;
else
  'no load data (holiday) for year:'==> p_year==>
endif;
;;; sending message to user if there is no weather information found.
endif;
endif;
Lend:
enddefine;

```

The following is load prediction for holidays when temperatures are used to correct the reference loads, used in pred_hol.

```

define pred_hol_cor.t(hol_date,n1,n2) → plist → act;
  vars hol_date,plist,act,e_list,rmserr;
  vars special_day,database_83,database_84;
  find_public_day_type(hol_date) → special_day;
  if special_day(2)="holiday" then
    pro_hol_cor.t(hol_date,n1,n2) → database_83 → database_84 → act
    → sat_85 → sun_85;
    post_hol(database_83,database_84,sat_85,sun_85) → plist;
  endif;
enddefine;

```

```

endif;
enddefine;

```

2) Prediction around time change-overs

The following procedures are used to predict loads around time change-overs.

```

;;; the c.type indicates the time to change from bst to gmt or from gmt
to bst.
define pred_change(hol_date,c.type,s.share) → pred_load → data_list
→ e_list → rmserr → e_max;
vars hol_date,pred_load,data_list,e_list,rmserr,e_max;
vars test_day,pred_load_t,data_list_t,pred_load_n,error_load;
vars item,error_rmserr;   ;;; variable declarartion.
hol_date(3) → year;
if present ([= = ^^c.type [??day ^year]]) then
  ;;; find the date of time change-overs this year.
  [^^day ^year] → day1;
  day_ndays_follow(day1,1) → new_day;
  day_ndays_follow(hol_date,0) → hol_date;
  if new_day(4)=hol_date(4) or
  hol_date(4)=new_day(4)+1 and hol_date(5)="sunday" then
    'around the time change-over: '==> c.type==>
    ;;; send message to user that the forecast day is around time change-over.
    day_ndays_follow(hol_date,-7) → ref_day;
    day_ndays_follow(hol_date,-1) → prev_day;
    if present ([== [^^ref_day ==] ?data_list_old == [^^prev_day ==]
    ?prev_data [^^hol_date ==] ?data_list ==]) then
      ;;; find the load (same day-of-week) before time change-over.
      if wea_database matches [== ^ref_day ?wea_inf1 ==] and
      wea_database matches [== [^^hol_date ==] ?wea_inf2 ==] then
        ;;; to search for weather information.
        'using data of last year as prediction: 1'==>
        'using data of this year only: 2'==>
        input_item( ) → item;
        if item=1 then
          bg_rg(c.type,hol_date,1) → load_gmt_ref
          → pred_load → load_ref.2 → load_a;
          ;;; refer to the load of the same period last year.
        else
          if hol_date(5)="monday" then
            pred_gb_monday(hol_date,c.type,s.share) → pred_load;
          else
            ;;; from new_day to hol_date-1.
            if member(hol_date(5),[saturday sunday]) then
              pred_bg_load(hol_date,c.type,s.share) → pred_load;
            end
          end
        end
      end
    end
  end
end

```

```

else
  pred_bg_load(hol_date,c_type,s_share) → pred_load_n;
  [%repeat 48 times 0 endrepeat%] → error_load;
  copylist(new_day) → test_day;
  0 → n;
l_b:
  pred_bg_old(test_day,c_type,s_share) → pred_load_t
  → data_list_t → e_list → rmserr → e_max;
  addup(error_load,difference(pred_load_t,data_list_t))
  → error_load;
  1+n → n;
  day_ndays_follow(test_day,1) → test_day;
  if test_day/=hol_date then
    goto l_b;
  endif;
  multiply(error_load,realof(1/n)) → error_load;
  difference(pred_load_n,error_load) → pred_load;
  ;;; errors of load prediction of previous days
  ;;; to correct the current prediction.
  endif;
endif;
endif;
else
  'no weather data available!'==>
endif;
'predict loads are:'==> pred_load==>
'actual loads are:'==> data_list==>
error_rmserr(pred_load,data_list) → e_list → rmserr → e_max;
'rms error over 24 hours is:'==> rmserr==>
'maximum error in percentage :'==> e_max==>
endif;
endif;
endif;
l_end:
enddefine;

```

The following procedure is used to predict loads around change-overs, but day-type is holiday, used in overall predictor.

```

define pred_change_hol(hol_date,c_type) → pred_load → data_list
→ e_list → rmserr → e_max;
  vars hol_date,pred_load,data_list,e_list,rmserr,e_max;
  vars year,special_day,day,day1,new_day,nyear,p_year,item;
  vars p_hol,date,change_date,weekth0,hol_date_ref,load_gmt_ref, load_ref_2;
  hol_date(3) → year;
  find_public_day_type(hol_date) → special_day;
  if special_day(2)="holiday" then
    'Today is holiday!'==> special_day(1)==>
    if present ([= = ^c_type [??day ^year]]) then
      [^^day ^year] → day1;
      day_ndays_follow(day1,1) → new_day;
      day_ndays_follow(hol_date,0) → hol_date;

```

```

if new_day(4)=hol_date(4) or
hol_date(4)=new_day(4)+1 and hol_date(5)="sunday" then
'around the time change-over: '==> c.type==>
'using the data of previous years as prediction: 1'==>
'using holiday rules to predict: 2'==>
input_item( ) → item;
if item=1 then
    1 → nyear;
ll:
    hol_date(3)-nyear → p_year;
    if present ([active holidays = [%special_day(1)% ??day ^p_year]]) then
        [^^day ^p_year] → p_hol;
        if member(p_hol(2),[3 4]) then
            if present ([= = ^^c_type [??date ^p_year]]) then
                [^^date ^p_year] → change_date;
                day_ndays.follow(change_date,1) → change_date;
                change_date(4) → weekth0;
                day_ndays.follow(p_hol,0) → hol_date_ref;
                if hol_date_ref(4)/=weekth0 then
                    nyear+1 → nyear;
                    if nyear<3 then
                        goto ll;
                    else
                        'no similar case in the past!'==>
                    endif;
                    ;;; to search for the same case in the historical data.
                else
                    bg_rg(c_type,hol_date,nyear) → load_gmt_ref
                    → pred_load → load_ref.2 → data_list;
                endif;
            endif;
        else
            nyear+1 → nyear;
            if nyear<3 then
                goto ll;
            else
                'no similar case in the past!'==>
            endif;
        endif;
    endif;
    else
        pred_hol(hol_date) → pred_load → data_list → e_list → rmserr;
    endif;
    'predict loads are:'==> pred_load==>
    'actual loads are:'==> data_list==>
    error_rmserr(pred_load,data_list) → e_list → rmserr → e_max;
    'rms error over 24 hours is:'==> rmserr==>
    'maximum error in percentage :'==> e_max==>
endif;
endif;
endif;
enddefine;

```

The following procedure, used in pred_change, is used to predict load

of Monday immediately after the time change-over. The procedure divides the overall load into two parts: lighting load, and the rest. The "s_share" is the basic load for lighting load, the shape of which is stored in the knowledge base.

```

define pred_gb_monday(hol_date,c_type,s_share) → pred_load;
  vars hol_date,year,day,ref_day,load_gmt,load_a,load_ref_2,load_gmt_ref;
  vars e_max,e_list,rmserr,c_type,prev_day,light_old,s_share;
  vars data_list_old,prev_data,load_r,l_1,mid_m,l_max,load_p,p_min,l_min;
  vars l_delt,day1,new_day,p_max,i,t;
  hol_date(3) → year;
  if present ([= = ^^c_type [??day ^year]]) then
    [^^day ^year] → day1;
    day_ndays_follow(day1,1) → new_day;
    day_ndays_follow(hol_date,0) → hol_date;
    if new_day(4)=hol_date(4) then
      'around the time change-over: '==> c_type==>
      day_ndays_follow(hol_date,-7) → ref_day;
      day_ndays_follow(hol_date,-1) → prev_day;
      if present ([== [^^ref_day ==] ?data_list_old == [^^prev_day ==]
?prev_data ==]) then
        if wea_database matches [== ^ref_day ?wea_inf1 ==] and
wea_database matches [== [^^hol_date ==] ?wea_inf2 ==] then
          if c_type=[bst.gmt] then
            bst_gmt_ps(light_old,s_share,data_list_old,wea_inf2,
wea_inf1) → pred_load;
            hd(rev(prev_data)) → load_r;
            load_r-500 → l_1; [^l_1] → mid_m;
            load_r → l_max; find_peak(pred_load) → load_p;
            hd(load_p(4)) → p_min; pred_load(p_min) → l_min;
            find_peak(prev_data) → load_p;
            hd(load_p(2)) → p_max; hd(load_p(4)) → p_min;
            realof(l_max-l_min)/(p_max-p_min+1) → l_delt;
            for i from 0 to (p_min-p_max-1) do
              l_max+i*l_delt → t;
              [^^mid_m ^t] → mid_m;
            endfor;
            [^^mid_m ^l_min] → mid_m;
            if p_min>p_max then
              allbutfirst(p_min-p_max,pred_load) → pred_load;
            endif;
            [^^mid_m ^^pred_load] → pred_load;
            ;;; to predict load when from bst changed to gmt.
          elseif c_type=[gmt.bst] then
            gmt_bst_ps(light_old,s_share,data_list_old,wea_inf2,
wea_inf1,fact) → pred_load;
            allbutfirst(46,prev_data) → t;
            [^^pred_load ^^t] → pred_load;
            ;;; to predict load when from gmt changed to bst.
          endif;
        else
          'no weather data available'==>
        endif;
      endif;
    endif;
  endif;
endif;

```

```

endif;
endif;
enddefine;

```

The procedure is used to predict loads of day which is not Monday but following the time change-over.

```

define pred_bg_load(hol_date,c_type,s_share) → pred_load;
vars hol_date,pred_load,data_list,e_list,rmserr,e_max;
day_ndays_follow(hol_date,-7) → ref_day;
day_ndays_follow(hol_date,-1) → prev_day;
if present ([== [^^ref_day ==] ?data_list_old == [^^prev_day ==]
?prev_data ==]) then
  if wea_database matches [== ^ref_day ?wea_inf1 ==] and
  wea_database matches [== [^^hol_date ==] ?wea_inf2 ==] then
    if c_type=[bst_gmt] then
      bst_gmt_ps(light_old,s_share,data_list_old,wea_inf2,wea_inf1)
      → pred_load;
      hd(rev(prev_data)) → load_r;
      load_r-500 → l_l; [^l_l] → mid_m;
      load_r → l_max; find_peak(pred_load) → load_p;
      hd(load_p(4)) → p_min; pred_load(p_min) → l_min;
      find_peak(prev_data) → load_p;
      hd(load_p(2)) → p_max; hd(load_p(4)) → p_min;
      realof(l_max-l_min)/(p_max-p_min+1) → l_delt;
      for i from 0 to (p_min-p_max-1) do
        l_max+i*l_delt → t;
        [^^mid_m ^t] → mid_m;
      endfor;
      [^^mid_m ^l_min] → mid_m;
      if p_min>p_max then
        allbutfirst(p_min-p_max,pred_load) → pred_load;
      endif;
      [^^mid_m ^^pred_load] → pred_load;
    elseif c_type=[gmt_bst] then
      gmt_bst_ps(light_old,s_share,data_list_old,wea_inf2,
      wea_inf1,fact) → pred_load;
      allbutfirst(46,prev_data) → t;
      [^^pred_load ^^t] → pred_load;
    endif;
  else
    'no weather data available!'=>
  endif;
endif;
enddefine;

```

3) Load disaggregation

The following procedures are used to fit curves to overall load.

```

define delt_load_pos_neg_max(week_day,t_database,load_delt, ini_d1_list,s_list,
s_type,load_tol,s_share,share_list,type,t_time_max,time_delt)
→ tn_database → load_delt_loc_ini;
vars week_day,t_database,load_delt,ini_d1_list,s_list,s_type,load_tol,s_share;
vars share_list,type,t_time_max,time_delt,tn_database,load_delt_loc_ini;
vars d1,d100,d11,d1100,d2,d200,d111,d11100,d222,d22200,sl_list,sll_list;
vars temp_load_list,new_s_list,load_delt_loc,load_delt_temp_list;
vars delt_list,t_time_max_list,p1,p2,pos_l,neg_l,delt,f1,u1,old,new;
vars cook_p1,temp_new_s_list,temp_d1_list,n_max_temp,load_max_temp;
vars n_min_temp,load_min_temp,load_delt_temp,f2,u2,cook_p2,n_s, t_time_max_n;
vars fact,res_in_com,tt_database;
vars delt_f,f_old,f_new,n1,n2;
t_database → [== [== [domestic cooking day]
[[norm = ?cook_p1 =] = [norm = ?cook_p2 =] ==] ==] ==];
t_database → [??d1 [??d11 ^s_type [??d111 ^^s_list ??d222] ] ??d2];
copylist(d1) → d100; copylist(d11) → d1100; copylist(d2) → d200;
copylist(d111) → d11100; copylist(d222) → d22200;
load_delt → load_delt_loc_ini;
cal_list(s_list) → sl_list;
multiply(sl_list,s_share) → sll_list;
addup(ini_d1_list,sll_list) → temp_load_list;
copylist(s_list) → new_s_list;
load_delt_loc_ini → load_delt_loc;
Lagain:
if s_type(1)/="street" then
new_s_list → [[posnorm ?f1 ?p1 ?u1] = [negnorm ?f2 ?p2 ?u2]];
[ ] → load_delt_temp_list;
[ ] → delt_list;
[ ] → t_time_max_list;
if s_type(1)/="industrial" then
if t_time_max < p1 then
true → pos_l;
false → neg_l;
for delt from -3 by -3 to (-time_delt) do
[ posnorm ^f1 ^p1 ^u1 ] → old;
[ posnorm ^f1 %p1+delt% ^u1 ] → new;
if s_type(1)="commercial" and cook_p1 ≥ new(3) then
goto l_cook_ind_max;
endif;
if (p1+delt) > 0 then
flat_curve(new_s_list,old,new) → temp_new_s_list;
cal_list(temp_new_s_list) → sl_list;
multiply(sl_list,s_share) → sll_list;
difference(temp_load_list,sll_list) → temp_d1_list;
max(1,(p1+delt-2*u1) div 6) → n1;
min(n1,(t_time_max div 6)) → n1;
min(48,(p2+2*u2) div 6) → n2;
max(n2,(t_time_max div 6)) → n2;
maximum_rang(temp_d1_list,n1,n2) → n_max_temp → load_max_temp;

```

```

    minimum_rang(temp_d1_list,n1,n2) → n_min_temp → load_min_temp;
    load_max_temp-load_min_temp → load_delt_temp;
    if load_min_temp>load_tol then
        [^^delt_list ^delt] → delt_list;
        [^^t_time_max_list ^n_max_temp] → t_time_max_list;
        [^^load_delt_temp_list ^load_delt_temp] → load_delt_temp_list;
    endif;
endif;
endif;
endif;
elseif t_time_max>p2 then
    true → neg_l;
    false → pos_l;
    for delt from 3 by 3 to (time_delt) do
        [negnorm ^f2 ^p2 ^u2] → old;
        [negnorm ^f2 %p2+delt% ^u2] → new;
        if s_type(1)="commercial" then
            if week_day="thursday" then
                if new(3)>240 then
                    goto Lw;
                endif;
            else
                if new(3)>216 then
                    goto Lw;
                endif;
            endif;
        endif;
        if (p2+delt)<288.1 then
            flat_curve(new_s_list,old,new) → temp_new_s_list;
            cal_list(temp_new_s_list) → sl_list;
            multiply(sl_list,s_share) → sll_list;
            difference(temp_load_list,sll_list) → temp_d1_list;
            max(1,(p1-2*u1) div 6) → n1;
            min(n1,(t_time_max div 6)) → n1;
            min(48,(p2+delt+2*u2) div 6) → n2;
            max(n2,(t_time_max div 6)) → n2;
            maximum_rang(temp_d1_list,n1,n2) → n_max_temp → load_max_temp;
            minimum_rang(temp_d1_list,n1,n2) → n_min_temp → load_min_temp;
            load_max_temp-load_min_temp → load_delt_temp;
            if load_min_temp>load_tol then
                [^^delt_list ^delt] → delt_list;
                [^^t_time_max_list ^n_max_temp] → t_time_max_list;
                [^^load_delt_temp_list ^load_delt_temp] → load_delt_temp_list;
            endif;
        endif;
    endif;
endif;
endif;
endif;
Lw:
    endif;
endif;
Lcook_ind_max:
    if length(load_delt_temp_list)>0 then
        minimum(load_delt_temp_list) → n_s → load_delt_temp;
        t_time_max_list(n_s) → n_max_temp;
        if load_delt_temp<load_delt_loc-10 then
            load_delt_temp → load_delt_loc;
            n_max_temp*6 → t_time_max;
            delt_list(n_s) → delt;
        endif;
    endif;
endif;

```

```

if pos_l then
  [posnorm ^f1 ^p1 ^u1] → old;
  [posnorm ^f1 %p1+delt% ^u1] → new;
  flat_curve(new_s_list,old,new) → new_s_list;
elseif neg_l then
  [negnorm ^f2 ^p2 ^u2] → old;
  [negnorm ^f2 %p2+delt% ^u2] → new;
  flat_curve(new_s_list,old,new) → new_s_list;
endif;
endif;
endif;
endif;
;;; changing u:
new_s_list → [[posnorm ?f1 ?p1 ?u1] ?d2 [negnorm ?f2 ?p2 ?u2]];
if t_time_max < p1 and t_time_max > (p1-2*u1-time_delt) then
  [[posnorm ^f1 ^p1 %u1+3%] ^d2 [negnorm ^f2 ^p2 ^u2]] → temp_new_s_list;
  cal_list(temp_new_s_list) → sl_list;
  multiply(sl_list,s_share) → sll_list;
  difference(temp_load_list,sll_list) → temp_d1_list;
  max(1,(p1-2*u1-6) div 6) → n1;
  min(n1,(t_time_max div 6)) → n1;
  min(48,(p2+2*u2) div 6) → n2;
  max(n2,(t_time_max div 6)) → n2;
  maximum_rang(temp_d1_list,n1,n2) → n_max_temp → load_max_temp;
  minimum_rang(temp_d1_list,n1,n2) → n_min_temp → load_min_temp;
  load_max_temp-load_min_temp → load_delt_temp;
  if load_delt_temp < load_delt_loc-10 and load_min_temp ≥ load_tol then
    load_delt_temp → load_delt_loc;
    copylist(temp_new_s_list) → new_s_list;
    n_max_temp*6 → t_time_max;
    goto l_again;
  endif;
elseif t_time_max > p2 and t_time_max < (p2+2*u2+time_delt) then
  [[posnorm ^f1 ^p1 ^u1] ^d2 [negnorm ^f2 ^p2 %u2+3%]] → temp_new_s_list;
  cal_list(temp_new_s_list) → sl_list;
  multiply(sl_list,s_share) → sll_list;
  difference(temp_load_list,sll_list) → temp_d1_list;
  max(1,(p1-2*u1) div 6) → n1;
  min(n1,(t_time_max div 6)) → n1;
  min(48,(p2+2*u2+6) div 6) → n2;
  max(n2,(t_time_max div 6)) → n2;
  maximum_rang(temp_d1_list,n1,n2) → n_max_temp → load_max_temp;
  minimum_rang(temp_d1_list,n1,n2) → n_min_temp → load_min_temp;
  load_max_temp-load_min_temp → load_delt_temp;
  if load_delt_temp < load_delt_loc-10 and load_min_temp ≥ load_tol then
    load_delt_temp → load_delt_loc;
    copylist(temp_new_s_list) → new_s_list;
    n_max_temp*6 → t_time_max;
    goto l_again;
  endif;
endif;
0.8 → delt_f;
lf_pn_u_p:
new_s_list → [[posnorm ?f_old ?p1 ?u1] = [negnorm = ?p2 ?u2]];
if t_time_max > (p1-2*u1) and t_time_max < (p2+2*u2) then

```

```

f_old*(1+delt_f) → f_new;
[posnorm ^f_old ^p1 ^u1] → old;
[posnorm ^f_new ^p1 ^u1] → new;
flat_curve(new_s_list,old,new) → temp_new_s_list;
cal_list(temp_new_s_list) → sl_list;
multiply(sl_list,s_share) → sll_list;
difference(temp_load_list,sll_list) → temp_d1_list;
max(1,(p1-2*u1) div 6) → n1;
min(n1,(t_time_max div 6)) → n1;
min(48,(p2+2*u2) div 6) → n2;
max(n2,(t_time_max div 6)) → n2;
maximum_rang(temp_d1_list,n1,n2) → n_max_temp → load_max_temp;
minimum_rang(temp_d1_list,n1,n2) → n_min_temp → load_min_temp;
load_max_temp-load_min_temp → load_delt_temp;
false → fact;
if load_delt_temp<load_delt_loc-10 and load_min_temp>load_tol then
  [^^d100 [^^d1100 ^s_type [^^d1100
    ^^temp_new_s_list ^^d22200]] ^^d200] → tt_database;
  constraint_ind_com(tt_database,share_list,type) → res_in_com;
  if not(res_in_com) then
    goto Lind_com_max;
  endif;
  cal_list(temp_new_s_list) → sl_list;
  multiply(sl_list,s_share) → sll_list;
  difference(temp_load_list,sll_list) → temp_d1_list;
  max(1,(p1-2*u1) div 6) → n1;
  min(n1,(t_time_max div 6)) → n1;
  min(48,(p2+2*u2) div 6) → n2;
  max(n2,(t_time_max div 6)) → n2;
  maximum_rang(temp_d1_list,n1,n2) → n_max_temp → load_max_temp;
  minimum_rang(temp_d1_list,n1,n2) → n_min_temp → load_min_temp;
  load_max_temp-load_min_temp → load_delt_temp;
  if load_delt_temp<load_delt_loc-10 and load_min_temp≥load_tol then
    load_delt_temp → load_delt_loc;
    copylist(temp_new_s_list) → new_s_list;
    n_max_temp*6 → t_time_max;
    true → fact;
  endif;
endif;
Lind_com_max:
  if not(fact) and delt_f≥0.02 then
    0.5*delt_f → delt_f;
    goto lf_pn_u_p;
  endif;
endif;
if load_delt_loc<load_delt_loc_ini-10 then
  load_delt_loc → load_delt_loc_ini;
  goto l_again;
endif;
[^^d100 [^^d1100 ^s_type [^^d1100 ^^new_s_list ^^d22200]] ^^d200]
→ tn_database;
enddefine;

```

```

define delt_load_norm_max(t_database,load_delt,ini_d1_list,s_list,load_tol,
sub_curve_list,share_list,type,s_type,s_share,t_time_max,time_delt)
→ tn_database → load_delt_loc_old;
vars t_database,load_delt,load_delt,ini_d1_list,s_list,load_tol;
vars sub_curve_list,s_type,s_share,tn_database,load_delt_loc_old, share_list,type;
vars d1,d100,d11,d1100,d2,d200,st1,st11,st2,st22,sl_list,sll_list;
vars temp_load_list,n_max,load_max,t_time_n,new_s_list,load_delt_loc,p1;
vars u1,delt_list,time_list,load_delt_temp_list,sign_delt,delt,p1_new,f1;
vars temp_new_s_list,temp_sub_curve_list,ind_p1,ind_p2,ind_cook_res,res1;
vars temp_d1_list,n_max_temp,load_max_temp,n_min_temp, load_min_temp;
vars n_s,t_time_max_n,delt_f,fact,f_old,f_new,tt_database, res_in_com,t2,res;
vars new_curve_list,n1,n2,load_delt_temp;
t_database → [== [== [industrial load day]
[= [posnorm = ?ind_p1 =] = [negnorm = ?ind_p2 =] ==] ==] ==];
t_database → [??d1 [??d11 ^s_type ^sub_curve_list] ??d2];
copylist(d1) → d100; copylist(d11) → d1100; copylist(d2) → d200;
sub_curve_list → [??st1 ^s_list ??st2];
copylist(st1) → st11; copylist(st2) → st22;
load_delt → load_delt_loc_old;
cal_list([ ^s_list]) → sl_list;
multiply(sl_list,s_share) → sll_list;
addup(ini_d1_list,sll_list) → temp_load_list;
maximum(temp_load_list) → n_max → load_max;
n_max*6 → t_time_n;
copylist(s_list) → new_s_list;
load_delt_loc_old → load_delt_loc;
Lagain:
new_s_list → [norm ?f1 ?p1 ?u1];
if abs(t_time_n-p1)<(2*u1+time_delt) then
[ ] → delt_list;
[ ] → time_list;
[ ] → load_delt_temp_list;
if abs(t_time_max-p1)<(2*u1+time_delt) then
sign(t_time_max-p1) → sign_delt;
if sign_delt/=0 then
for delt from sign_delt*3 by sign_delt*3 to
sign_delt*(min(time_delt,abs(t_time_max-p1)+3)) do
delt+p1 → p1_new;
if p1_new>0 and p1_new<288 then
[norm ^f1 ^p1_new ^u1] → temp_new_s_list;
if s_type(1)="cooking" then
[^st11 ^temp_new_s_list ^^st22] → temp_sub_curve_list;
constraint_ind_cook(ind_p1,ind_p2,
temp_sub_curve_list,temp_new_s_list) → ind_cook_res;
if not(ind_cook_res) then
goto lc1;
endif;
endif;
cooking_time_constraint(s_type,s_list,temp_new_s_list,
sub_curve_list,ind_p1,ind_p2) → res1;
if not(res1) then
goto lc1;
endif;
cal_list([ ^temp_new_s_list]) → sl_list;
multiply(sl_list,s_share) → sll_list;

```

```

    difference(temp_load_list,sll_list) → temp_d1_list;
    max(1,(p1+delt-2*u1) div 6) → n1;
    min(n1,(t_time_max div 6)) → n1;
    min(48,(p1+delt+2*u1) div 6) → n2;
    max(n2,(t_time_max div 6)) → n2;
    maximum_rang(temp_d1_list,n1,n2) → n_max_temp → load_max_temp;
    minimum_rang(temp_d1_list,n1,n2) → n_min_temp → load_min_temp;
    load_max_temp-load_min_temp → load_delt_temp;
    if load_min_temp>load_tol then
        [^^delt_list ^delt] → delt_list;
        [^^time_list ^n_max_temp] → time_list;
        [^^load_delt_temp_list ^load_delt_temp] → load_delt_temp_list;
    endif;
endif;
endif;
endif;
lcl:
    if length(load_delt_temp_list)>0 then
        minimum(load_delt_temp_list) → n_s → load_delt_temp;
        time_list(n_s) → n_max_temp;
        if load_delt_temp<load_delt_loc-10 then
            load_delt_temp → load_delt_loc;
            delt_list(n_s) → delt;
            n_max_temp*6 → t_time_max;
            [norm ^f1 %p1+delt% ^u1] → new_s_list;
        endif;
    endif;
endif;
endif;
endif;
;;; changing u:
0.8 → delt_f;
new_s_list --> [norm ?f1 ?p1 ?u1];
if abs(t_time_max-p1)≤(2*u1+time_delt) then
    copylist(new_s_list) → temp_new_s_list;
    temp_new_s_list(4)+3 → temp_new_s_list(4);
    cal_list([temp_new_s_list]) → sl_list;
    multiply(sl_list,s_share) → sll_list;
    difference(temp_load_list,sll_list) → temp_d1_list;
    max(1,(p1-2*u1-6) div 6) → n1;
    min(n1,(t_time_max div 6)) → n1;
    min(48,(p1+2*u1+6) div 6) → n2;
    max(n2,(t_time_max div 6)) → n2;
    maximum_rang(temp_d1_list,n1,n2) → n_max_temp → load_max_temp;
    minimum_rang(temp_d1_list,n1,n2) → n_min_temp → load_min_temp;
    load_max_temp-load_min_temp → load_delt_temp;
    if load_delt_temp<load_delt_loc-10 and load_min_temp≥load_tol then
        load_delt_temp → load_delt_loc;
        n_max_temp*6 → t_time_max;
        copylist(temp_new_s_list) → new_s_list;
        goto Lagain;
    endif;
endif;
endif;
lf2:
    new_s_list --> [norm ?f_old ?p1 ?u1];
    false → fact;

```

```

if abs(p1-t.time_max)<2*u1 then
  f_old*(1+delt.f) → f_new;
  [norm ^f_new ^p1 ^u1] → temp_new_s_list;
  cal_list([temp_new_s_list]) → sl_list;
  multiply(sl_list,s_share) → sll_list;
  difference(temp_load_list,sll_list) → temp_d1_list;
  max(1,(p1-2*u1) div 6) → n1;
  min(n1,(t.time_max div 6)) → n1;
  min(48,(p1+2*u1) div 6) → n2;
  max(n2,(t.time_max div 6)) → n2;
  maximum_rang(temp_d1_list,n1,n2) → n_max_temp → load_max_temp;
  minimum_rang(temp_d1_list,n1,n2) → n_min_temp → load_min_temp;
  load_max_temp-load_min_temp → load_delt_temp;
  if load_delt_temp<load_delt_loc-10 and load_min_temp≥load_tol then
    [^^d100 [^^d1100 ^s_type [^^st1 ^temp_new_s_list ^^st2]] ^^d200]
    → tt_database;
    constraint_ind_com(tt_database,share_list,type) → res_in_com;
    if not(res_in_com) then
      goto l_ind_com_max;
    endif;
    if s_type(1)="cooking" then
      if sub_curve_list matches [^s_list ??t2] then
        [temp_new_s_list ^^t2] → temp_sub_curve_list;
        constraint_cook_fac(temp_sub_curve_list) → res → new_curve_list;
        if not(res) then
          copylist(hd(new_curve_list)) → new_s_list;
          goto l_ind_com_max;
        endif;
      elseif sub_curve_list matches [??t2 ^s_list] then
        [^^t2 ^temp_new_s_list] → temp_sub_curve_list;
        constraint_cook_fac(temp_sub_curve_list) → res → new_curve_list;
        if not(res) then
          copylist(hd(rev(new_curve_list))) → new_s_list;
          goto l_ind_com_max;
        endif;
      endif;
    endif;
    load_delt_temp → load_delt_loc;
    n_max_temp*6 → t.time_max;
    copylist(temp_new_s_list) → new_s_list;
    true → fact;
  endif;
l_ind_com_max:
  if not(fact) and delt.f≥0.02 then
    0.5*delt.f → delt.f;
    goto lf2;
  endif;
endif;
if load_delt_loc<load_delt_loc_old-10 then
  load_delt_loc → load_delt_loc_old;
  goto l_again;
endif;
[^^d100 [^^d1100 ^s_type [^^st11 ^new_s_list ^^st22]] ^^d200]
→ tn_database;
enddefine;

```

The following procedure is used to fit curves of pos-neg, norm, in order to minimise the load_delt.

```

define delt_load_fit_curve(day,type,data_list,share_list,share_step,
time_delt) → temp_database → share_list → load_delt_old;
  vars day,type,data_list,share_list,share_step,temp_database;
  vars share_list,load_delt_old,load_delt_loc,load_tol;
  vars in_load_max,load_max_old,temp_database;
  vars load_max,week_day,n_max,load_max,curve_list,ini_d1_list;
  vars n_min,load_min,time_delt,load_delt;
  vars t_time_max,p_pos_neg_list,pos_neg_list,type_pos_neg_list;
  vars l_pos_neg,pos_neg_load_delt,temp_database_list;
  vars n_l,n_p_x,s_list,s_type,d1,s_share;
  vars load_max_t,tn_database,d2,n_load;
  vars t_time_min,p_norm_list,norm_list;
  vars type_norm_list,norm_list_all,length_norm,norm_load_delt;
  vars sub_curve_list,load_delt_x,temp_database_t;
  day(5) → week_day;
  add_normal_state(day,type) → temp_database;
  ;;; to form original components.
  maximum(data_list) → n_max → load_max;
  2*share_step → load_tol;
  delt_load_find_share(type,data_list,share_list,share_step, temp_database,
  load_tol,load_max) → curve_list → share_now → share_list → ini_d1_list;
  maximum(ini_d1_list) → n_max → load_max;
  minimum(ini_d1_list) → n_min → load_min;
  load_max-load_min → load_delt_old;
  load_delt_old → load_delt;
l_pos_neg_max:
  ;;; change pos-neg curves in order to minimise (max(residuals)-min(residuals)).
  delt_load_find_share(type,data_list,share_list,share_step, temp_database,
  load_tol,load_delt) → curve_list → share_now → share_list → ini_d1_list;
  maximum(ini_d1_list) → n_max → load_max;
  n_max*6 → t_time_max;
  minimum(ini_d1_list) → n_min → load_min;
  load_max-load_min → load_delt;
  find_chang_order_pos_neg(curve_list,share_now,type,t_time_max,time_delt)
  → p_pos_neg_list → pos_neg_list → type_pos_neg_list;
  length(p_pos_neg_list) → l_pos_neg;
  if l_pos_neg>0 then
    [ ] → pos_neg_load_delt;
    [ ] → temp_database_list;
  until p_pos_neg_list=[ ] do
    maximum(p_pos_neg_list) → n_l → n_p_x;
    pos_neg_list(n_l) → s_list;
    type_pos_neg_list(n_l) → s_type;
    type → [??d1 ^s_type ??d2];
    share_list(length(d1)+1) → s_share;
    delt_load_pos_neg_max(week_day,temp_database,load_delt, ini_d1_list,
    s_list,s_type,load_tol,s_share,share_list,type, t_time_max,time_delt) → tn_database
    → load_delt_loc;
    pos_neg_list → [??d1 ^s_list ??d2];
    [^^d1 ^^d2] → pos_neg_list;
    type_pos_neg_list → [??d1 ^s_type ??d2];
  
```

```

[^^d1 ^^d2] → type_pos_neg_list;
p_pos_neg_list → [??d1 ^n_p_x ??d2];
[^^d1 ^^d2] → p_pos_neg_list;
[^^pos_neg_load_delt ^load_delt_loc] → pos_neg_load_delt;
[^^temp_database_list ^tn_database] → temp_database_list;
enduntil;
until pos_neg_load_delt=[] do
  minimum(pos_neg_load_delt) → n_load → load_delt_x;
  copylist(temp_database_list(n_load)) → temp_database_t;
  if load_delt_x<load_delt_old-10 then
    res_load(temp_database_t,data_list,type,share_list) → d1_list;
    maximum(d1_list) → n_max → load_max;
    minimum(d1_list) → n_min → load_min;
    load_max-load_min → load_delt;
    if load_delt<load_delt_old-10 and load_min≥load_tol then
      load_delt → load_delt_old;
      copylist(temp_database_t) → temp_database;
      goto l_pos_neg_max;
    endif;
    pos_neg_load_delt → [??d1 ^load_delt_x ??d2];
    [^^d1 ^^d2] → pos_neg_load_delt;
    temp_database_list → [??d1 ^temp_database_t ??d2];
    [^^d1 ^^d2] → temp_database_list;
  else
    goto l_next1;
  endif;
enduntil;
endif;
l_next1:
load_delt_old → load_delt;
delt_load_find_share(type,data_list,share_list,share_step,temp_database,
load_tol,load_delt) → curve_list → share_now → share_list → ini_d1_list;
maximum(ini_d1_list) → n_max → load_max;
minimum(ini_d1_list) → n_min → load_min;
n_min*6 → t_time_min;
load_max-load_min → load_delt;
find_chang_order_pos_neg(curve_list,share_now,type,t_time_min, time_delt)
→ p_pos_neg_list → pos_neg_list → type_pos_neg_list;
length(p_pos_neg_list) → l_pos_neg;
if l_pos_neg>0 then
  [ ] → pos_neg_load_delt;
  [ ] → temp_database_list;
  until p_pos_neg_list=[ ] do
    maximum(p_pos_neg_list) → n_l → n_p_x;
    pos_neg_list(n_l) → s_list;
    type_pos_neg_list(n_l) → s_type;
    if s_type(1)/="industrial" then
      type → [??d1 ^s_type ??d2];
      share_list(length(d1)+1) → s_share;
      delt_load_pos_neg_min(temp_database,load_delt,
ini_d1_list,s_list,s_type,load_tol,s_share,share_list, type,t_time_min,
time_delt) → tn_database → load_delt_loc;
      [^^pos_neg_load_delt ^load_delt_loc] → pos_neg_load_delt;
      [^^temp_database_list ^tn_database] → temp_database_list;
    endif;
  enduntil;
endif;

```

```

pos_neg_list --> [??d1 ^s_list ??d2];
[^d1 ^^d2] → pos_neg_list;
type_pos_neg_list --> [??d1 ^s_type ??d2];
[^d1 ^^d2] → type_pos_neg_list;
p_pos_neg_list --> [??d1 ^n_p_x ??d2];
[^d1 ^^d2] → p_pos_neg_list;
enduntil;
until pos_neg_load_delt=[] do
  minimum(pos_neg_load_delt) → n_load → load_delt_x;
  copylist(temp_database_list(n_load)) → temp_database_t;
  if load_delt_x<load_delt_old-10 then
    res_load(temp_database_t,data_list,type,share_list) → d1_list;
    maximum(d1_list) → n_max → load_max;
    minimum(d1_list) → n_min → load_min;
    load_max-load_min → load_delt;
    if load_delt<load_delt_old-10 and load_min≥load_tol then
      load_delt → load_delt_old;
      copylist(temp_database_t) → temp_database;
      goto l_pos_neg_max;
    endif;
    pos_neg_load_delt --> [??d1 ^load_delt_x ??d2];
    [^^d1 ^^d2] → pos_neg_load_delt;
    temp_database_list → [??d1 ^temp_database_t ??d2];
    [^^d1 ^^d2] → temp_database_list;
  else
    goto l_next2;
  endif;
enduntil;
endif;
;;; to change norm curves so that the objective function is locally minimised.
l_next2:
load_delt_old → load_delt;
del_load_find_share(type,data_list,share_list,share_step,temp_database,
load_tol,load_delt) → curve_list → share_now → share_list → ini_d1_list;
maximum(ini_d1_list) → n_max → load_max;
n_max*6 → t_time_max;
minimum(ini_d1_list) → n_min → load_min;
load_max-load_min → load_delt;
find_chang_order_norm(curve_list,share_now,type,t_time_max,time_delt)
→ p_norm_list → norm_list → type_norm_list → norm_list_all;
length(p_norm_list) → length_norm;
if length_norm>0 then
  [ ] → norm_load_delt;
  [ ] → temp_database_list;
  until p_norm_list=[ ] do
    minimum_abs(p_norm_list) → n_l → n_p_x;
    if n_p_x<time_delt then
      norm_list(n_l) → s_list;
      type_norm_list(n_l) → s_type;
      type --> [??d1 ^s_type ??d2];
      share_list(length(d1)+1) → s_share;
      norm_list_all(n_l) → sub_curve_list;
      delt_load_norm_max(temp_database,load_delt,ini_d1_list,s_list,
load_tol,sub_curve_list,share_list,type,s_type,s_share,t_time_max,
time_delt) → tn_database → load_delt_loc;

```

```

norm_list --> [??d1 ^s_list ??d2];
[^d1 ^^d2] → norm_list;
type_norm_list --> [??d1 ^s_type ??d2];
[^d1 ^^d2] → type_norm_list;
p_norm_list --> [??d1 ^n_p_x ??d2];
[^d1 ^^d2] → p_norm_list;
norm_list_all --> [??d1 ^sub_curve_list ??d2];
[^d1 ^^d2] → norm_list_all;
[^norm_load_delt ^load_delt_loc] → norm_load_delt;
[^temp_database_list ^tn_database] → temp_database_list;
else
  goto l_next3;
endif;
enduntil;
until norm_load_delt=[ ] do
  minimum(norm_load_delt) → n_load → load_delt_x;
  copylist(temp_database_list(n_load)) → temp_database_t;
  if load_delt_x < load_delt_old - 10 then
    res_load(temp_database_t, data_list, type, share_list) → d1_list;
    maximum(d1_list) → n_max → load_max;
    minimum(d1_list) → n_min → load_min;
    load_max - load_min → load_delt;
    if load_delt < load_delt_old - 10 and load_min ≥ load_tol then
      load_delt → load_delt_old;
      copylist(temp_database_t) → temp_database;
      goto l_pos_neg_max;
    endif;
    norm_load_delt --> [??d1 ^load_delt_x ??d2];
    [^^d1 ^^d2] → norm_load_delt;
    temp_database_list --> [??d1 ^temp_database_t ??d2];
    [^^d1 ^^d2] → temp_database_list;
  else
    goto l_next3;
  endif;
enduntil;
endif;
l_next3:
load_delt_old → load_delt;
delt_load_find_share(type, data_list, share_list, share_step, temp_database,
load_tol, load_delt) → curve_list → share_now → share_list → ini_d1_list;
maximum(ini_d1_list) → n_max → load_max;
minimum(ini_d1_list) → n_min → load_min;
n_min * 6 → t_time_min;
load_max - load_min → load_delt;
find_chang_order_norm(curve_list, share_now, type, t_time_min, time_delt)
→ p_norm_list → norm_list → type_norm_list → norm_list_all;
length(p_norm_list) → length_norm;
if length_norm > 0 then
  [ ] → norm_load_delt;
  [ ] → temp_database_list;
  until p_norm_list=[ ] do
    minimum_abs(p_norm_list) → n_l → n_p_x;
    norm_list(n_l) → s_list;
    type_norm_list(n_l) → s_type;
    type --> [??d1 ^s_type ??d2];
  enduntil;
endif;

```

```

share_list(length(d1)+1) → s_share;
norm_list_all(n_l) → sub_curve_list;
delt_load_norm_min(temp_database,load_delt,ini_d1_list,s_list,
load_tol,sub_curve_list,s_type,s_share,t_time_min,time_delt)
→ tn_database → load_delt_loc;
norm_list → [??d1 ^s_list ??d2];
[^d1 ^d2] → norm_list;
type_norm_list → [??d1 ^s_type ??d2];
[^d1 ^d2] → type_norm_list;
p_norm_list → [??d1 ^n_p_x ??d2];
[^d1 ^d2] → p_norm_list;
norm_list_all → [??d1 ^sub_curve_list ??d2];
[^d1 ^d2] → norm_list_all;
[^norm_load_delt ^load_delt_loc] → norm_load_delt;
[^temp_database_list ^tn_database] → temp_database_list;
enduntil;
until norm_load_delt=[] do
minimum(norm_load_delt) → n_load → load_delt_x;
copylist(temp_database_list(n_load)) → temp_database_t;
if load_delt_x<load_delt_old-10 then
res_load(temp_database_t,data_list,type,share_list) → d1_list;
maximum(d1_list) → n_max → load_max;
minimum(d1_list) → n_min → load_min;
load_max-load_min → load_delt;
if load_delt<load_delt_old-10 and load_min≥load_tol then
load_delt → load_delt_old;
copylist(temp_database_t) → temp_database;
goto l_pos_neg_max;
endif;
norm_load_delt → [??d1 ^load_delt_x ??d2];
[^d1 ^d2] → norm_load_delt;
temp_database_list → [??d1 ^temp_database_t ??d2];
[^d1 ^d2] → temp_database_list;
else
goto l_next4;
endif;
enduntil;
endif;
l_next4:
enddefine;

```

The following rule is used to estimate Christmas-day holiday load:

If it is a Christmas-day holiday,
And it is a Sunday,
Then the holiday correction factor is 1.10.

