MODELLING AND FORECASTING ENERGY DEMAND
USING METEOROLOGICAL DATA

By

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DECLARATION

This thesis, submitted for the degree of Ph.D., has been written entirely by myself, and represents work performed only by myself.

Meteorology Dept.

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Statistical methods, including multiple time series analysis, are used to develop diagnostic models relating energy usage to meteorological factors for a variety of time and space scales as well as for different energy sources. These models demonstrate the importance of hitherto ignored meteorological variables in the explanatory components of linear models for the space and time variation of energy demand.

Based on the results of diagnostic case studies, a daily forecasting model of regional electricity and gas demand has been formulated and tested using real data. These tests include random simulation of weather forecast errors. This model incorporates parametric measures of effective temperature, windchill, sunshine, rainfall and visibility, and is used to illustrate the importance of these factors and their synoptic as well as mesoscale variability in achieving good predictibility. Synoptic-scale case studies are used to illustrate model deficiencies on occasions of extreme demand.
A SELECTIVE REFERENCE LIST OF VARIABLES

With Units and Abbreviations

Meteorological Parameters (to accompany Chapters 5 and 6)

CPW: Cooling power of the wind (windchill), knots**k.deg C
k: Exponent of windspeed in CPW expression
MCF: Misery correction factor, SRV units/-deg C.
RD: Daily rainfall duration at Glasgow airport, mins
SRV: Empirical SUN-RD-VIS (misery) index, dimensionless
SUN: Daily sunshine hours at Glasgow or Heathrow
TA: Actual daily temperature (weighted), Glasgow/Gatwick
TCOMF: Comfort temperature
TE: Effective temperature (exponentially smoothed TA)
TDEV: Deviations of TE from seasonal TE (i.e. TE residuals)
U: Daily mean windspeed (weighted), Glasgow/Gatwick, knots
VIS: Daily mean visibility at Glasgow, kilometres (km)
WCF: Wind correction factor, knots/-deg C.

Energy Variables (to accompany all Chapters)

BGC: British Gas Corporation, HG London
DDEV: Deviations of DWD from seasonals (i.e. DWD residuals)
DoE: Department of Energy (Central Government)
DoHC: Day-of-week-correction
DWD: Deweeked demand
MWh: Megawatt-hours (=1000 KWh, 1 KWh = 3.6 MegaJoules)
NTGAS: North Thames Gas Board, HG London
RAW: Raw daily electricity or gas demand
SGAS: Scottish Gas Region, HG Edinburgh
SEE: South-East Electricity Board, HG Brighton
SSEB: South Scotland Electricity Board, HG Glasgow
T.Th: 1000 Therms (1 Therm = 29.3 KWh)

Statistical Parameters (to accompany all Chapters, but especially 5 and 6)

Acf: Autocorrelation function (lag r)
a, b, c, d: Linear and multivariate model coefficients
E: Expected number of turning points (if random)
ENR: Effective number of repetitions
FE: Demand forecast error = actual(RAW) - forecast(FC)
FE(1), FE(2), FE(3): Mean actual or mean absolute (modulus) FE
when using 1 variable, i.e. only TDEV
when using 2 variables: TDEV and CPW
when using 3 variables: TDEV, CPW and SRV
n: Number of independent values
N: Total sample size
rms PC: Root mean square % forecast error
r: Linear or multiple cross correlation coefficient
r**2: Coefficient of determination (% variance explained)
RE: Residual error = Actual - postdicted demand
RE(1), RE(2), RE(3): As FE(1), etc, but using RE
SEE: Standard error of estimate (rms RE)
t: Test statistic for testing significance of r
z: Test statistic for testing whether RAW = FC
Zo: Test statistic for testing whether FE = 0
Z: Fishers Z transformation, for difference of r's
CHAPTER 1
INTRODUCTION AND LITERATURE SURVEY

1.1. PHILOSOPHY OF THE APPROACH
1.1.1. MOTIVATION AND PURPOSE

At the flick of a switch or the press of a button, we have instantaneous heat, light or power at our command. This continuing miracle is often taken for granted. Our demands for energy (natural gas, electricity, coal and oil) need to be predicted to ensure continued supply and hence to maintain the necessary standards of thermal comfort. This desirable condition becomes particularly important in winter in this country, for space-heating and lighting. In some climates, space-cooling by air conditioning is also necessary in summer.

Such demands for energy are closely controlled by the weather, amongst many other factors. Every day, therefore, the Electricity and Gas Boards have to make a prediction of the following day’s demand, and use weather forecasts to do so. The main goal of this thesis is to model the effects of meteorological parameters on energy consumption, and thence to predict future demands using meteorological data. This is a very important and real practical problem in modern-day energy management. The greatest motivation to undertake a fresh look at such an old problem came partly from the attitudes of the power industries themselves, and was also initially inspired by Central Government (Department of Energy). The Meteorology Department at Edinburgh University felt it to be a promising avenue of research, and so applied to the Natural Environment Research Council for support, and asked the Department Of Energy (Economics and Statistics Division) to collaborate.

The need for such specific attention, and for a more general re-examination of the use of meteorological data, was gleaned from a variety of meetings of the author with the fuel industries (Area Electricity and Gas Boards and Department of Energy) through personal or indirect communication. The views expressed here are indirectly

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collated/ inferred from these personal meetings, but are those of the author. They do not reflect any opinions of the energy authorities concerned. As a rewarding consequence of such visits, the work has important applications in the field of energy conservation management, where considerable monetary savings are potentially possible. Even more encouragingly, parts of the present study have significant real-time applications for on-line demand forecasting.

The work naturally falls into two quite distinct, though complementary parts: statistical modelling of weather-demand relations to understand consumer response, and prediction of energy consumption using meteorological forecasts. This is investigated here on a variety of time and space scales. The greatest contribution of the thesis lies in the development from scratch of a totally operational daily forecasting model of regional electricity and gas demand, using several novel parameterisations of the meteorology. Though the climax of the work lies here, other time and space scales involving coal and oil are studied to support these later studies. The thesis offers a unique combination of many types of evidence to complement the statistics; these include graphical/visual, and synoptic evidence. Results will normally be presented in both tabular and graphical form. Many of the techniques to be used are believed to be original.

The statistical analysis of energy and meteorological data in itself forms an important part of the overall contribution, and there are some unique applications of such knowledge. The modelling of energy-weather relations brings together atmospheric science and statistics. The word “modelling” is used throughout to mean “statistical modelling”, as distinct from numerical modelling, and by this we mean the explicit construction of functional mathematical/statistical relationships between energy demand and weather. Likewise, by “energy-modelling” we shall be referring to the mathematical modelling of “energy-weather” or “energy-meteorology” relationships.

Chapter 2 will introduce and illustrate the statistical techniques to be used, and will undertake a
comprehensive discussion of the relevant statistical theory of multiple time series analysis. The body of the thesis will then be devoted to case studies of modelling energy demand on various scales, though it is not until Chapter 5 that any forecasting will be undertaken.

1.1.2. THE QUESTION OF SCALE (SPATIAL/TEMPORAL HIERARCHIES)

Central to any notion of statistical modelling is the concept of scale, or a "hierarchy" of scales or "orders". In a spatial context, these can be regarded as levels of aggregation (of consumers), which vary from individual family homes to whole nations, through several intermediate space scales. In the time domain we will always be dealing with multiple discrete time series, the scale ranging from monthly or annual down to daily and hourly. A decomposition theory, which will allow us to break down the series into separate components on different time scales, will be described in Chapter 2.

The present study covers several temporal and spatial scales. Chapter 3 summarises the results of an investigation of monthly coal and oil consumption on a national basis. This is a relatively coarse level of aggregation to begin with, but it is a necessary part of the lead up in understanding finer scales. It also serves to conveniently provide illustrations of the statistical methods, their usefulness and problems. Having recognised and overcome these problems, we then proceed to a finer scale. Chapter 4 presents the results of a local case study of weekly gas and oil consumption for two individual groups of buildings. This is a fine spatial level of aggregation, but is still a fairly coarse time scale. This too is part of the necessary build up.

Chapters 5 and 6 are really the climax or core of the work, and this is where forecasting daily electricity and gas demand is achieved to a high degree of accuracy. This phase contains results at their most encouraging and useful, having real practical value and worthwhile savings. In some ways, Chapters 3 and 4 effectively play a supporting role for the daily case studies in Chapters 5 and 6.
In Chapter 5, the development of an original forecasting model for daily electricity and gas consumption is described in detail. Chapter 6 then applies this to some English and Scottish regional case studies (four in all). In them, the influence of other meteorological parameters, in addition to temperature, are uncovered. These include windspeed, rainfall, solar radiation and visibility, amongst others. This part also contains the first attempt (to the author's knowledge) made to bring out the importance of synoptic situation, especially extreme/sudden synoptic and mesoscale events. It is indeed very surprising that no such studies of synoptic or mesoscale situation and energy demand have appeared, especially since severe or sudden weather events are of great interest to short-term energy planners and forecasting engineers.

The model derived here is totally operational and has important practical applications. This forms an overlap with energy conservation management, but the concept of energy conservation is only briefly touched upon elsewhere in the thesis, notably Chapter 4. The concluding Chapter then follows, which undertakes a critical evaluation of the daily model and suggests possible refinements. The work is then related to the broader term aims of energy modelling and the field as a whole, so as to place this study in the context of the pre-existing body of knowledge. Individual conclusions to each Chapter are presented separately therein. The work is thus presented as a comprehensive study of modelling energy demand on several scales. The whole presentation is structured to show successive improvements in model sophistication and usefulness, as we consider increasingly fine time scales.

It is believed that a consideration of several time and space scales is desirable, since time and space scale do interact. For example, it is many thousands of local microscale consumer responses to weather that make up the regional total or the national level of aggregation ("nesting" of scales). Similarly for the temporal hierarchy, monthly or weekly (intra-seasonal) reactions to weather are composed of many individual responses on the daily time
scale. Integration of scale allows deeper understanding of the nature of customer response. In summary, small scale spatial reactions are smoothed out or lost by averaging over a region. Likewise, on translation to a temporal context, daily responses are averaged out or filtered out with coarse time scales. This concept of scale translation and hierarchies will prove useful later, since we would expect the same laws operating at the local level to also manifest themselves at the next level of aggregation up, i.e. on the sub-regional to national scales.

1.1.3 PHYSICAL INTERPRETATION AND THE STATISTICAL APPROACH

The overall study represents a compromise linking theory with applied statistics and meteorology. It manages to accomplish this by basing the statistical techniques on firm physical foundations, and by emphasizing the importance of physical interpretation of results. Theory and practice can then become complementary. The study puts forward a unique combination of statistical analysis and meteorological physics. This marriage of two distinctly separate fields, and the ensuing emphasis on physical meaning, will prove to be a central theme throughout. The advantage of the statistical approach is that it can be made highly rigorous, but physical meaning should never be divorced from such theory. Rose (1949) reminds us that "...we must beware of the fallacy of reading more into the results than they contain...".

The sensitivity of the statistical approach to time and space scale will prove to be of crucial importance. In pure statistics, the whole idea of physical meaning is completely overlooked in favour of highly theoretical considerations. It is strongly maintained here that understanding of the underlying meteorological fundamentals should supersede the importance of pure statistics. Energy and meteorological data possess unique properties, and techniques for handling them are specialised and to some extent peculiar to this field, hence the necessity of the statistical chapter (Chapter 2).
1.1.4. GENERAL ASPECTS OF ENERGY MANAGEMENT

Weather conditions play an important part in the decision-making process of many weather-sensitive enterprises. Such sectors of the economy include agriculture, aviation, social leisure and recreation, sports and entertainment, government, industry (e.g. construction), transport and last but not least energy. The electricity, gas, coal and some of the oil industry in Britain are all under public ownership. These are weather-sensitive to differing extents, and make varying use of meteorological information in several direct and indirect ways. For example, the electricity and gas industries have contracts with the Meteorological Office for the frequent receipt of weather forecasts to help them predict demand. All of these nationalised fuel industries have a centralised control of production, transmission and distribution.

The Central Electricity Generating Board (CEGB) is responsible for generating, distributing and selling electricity to the Area Boards. Electricity is generated in conventional thermal (coal- or oil-fired) power stations, hydro-electric or nuclear power stations. The Electricity Council and National Control co-ordinate this integrated system. Hydro-electric power systems include free running and pumped storage schemes, and are mainly confined to Scotland and Wales. They use weather forecasts in the form of medium and long term rainfall predictions for catchment hydrology, flood control studies and reservoir design, see Tress (1979), B.Sc thesis, for drainage basin hydrology/meteorology and morphometry. A nuclear power program, despite the controversy of its environmental, public health, social safety and political/military issues, has been in progress since 1955. Accordingly, British Nuclear Fuels Ltd (BNFL) and United Kingdom Atomic Energy Authority (UKAEA) feed power into the national grid. This is mostly weather-insensitive base load for industry.

Similarly, British Gas co-ordinates the flow and sales of natural (North Sea) gas within its 12 Regions. There is massive capital investment in the coal and offshore (North Sea) oil industries, dominated by the National Coal Board.
(NCB) and the large oil companies. Alternative, renewable energy sources, such as solar, tidal, geothermal, waves and wind power, will be ignored here, but see Tress (1980), M.Sc Thesis, on the influence of meteorology on solar, wind and wave energy, or Duncan (1977) on solar and wind power.

In contrast to the state ownership of the British power industries, many of the American public utilities (as they tend to be called there) are privately owned, in keeping with the capitalist system. This leads to several interesting differences in research history and tradition, as we shall see.

1.1.5. WEATHER SENSITIVITY OF ENERGY IN GENERAL

It has long been recognised that temperature is the most important weather variable affecting power consumption. Many previous investigations have confined their attention to this. The present study also conclusively demonstrates the influence of windspeed, windchill, sunshine, perceived temperature, rainfall and visibility. The whole field is relatively underdeveloped, and though several modelling studies have arisen concerning such variables, few have used them in demand prediction applications.

The heating load is closely controlled by air temperature, but also by windspeed via free ventilation/infiltration (draught-induced heating demand). The lighting component (for electricity demand) is dictated by daylight illumination which is a function of cloud cover, sunshine and visibility (and possibly precipitation, see later).

The heating component consists of space- and water-heating (central heating and individual fires) and is very significant in this country during the "heating season" (Sep-May). In hotter climates it also becomes desirable to cool buildings in summer (the "cooling season"), and such places have appreciable space cooling loads, met by air conditioning, refrigeration and fans for forced ventilation.

Energy is sold to and used by a very wide variety of customers. These fall into three basic categories: "domestic", "industrial" and "commercial". This customer class breakdown of the energy market is termed "load-mix".
The domestic sector comprises family homes, farms, flats and other private residential dwellings. The commercial sector includes shops, offices, banks, schools, hospitals and places of entertainment. The industrial sector forms part of the weather-insensitive "base load". A detailed customer categorisation is given in Appendix 1 (in both tabular and pie-chart form), which the reader will find interesting and useful to refer to throughout. This will not be discussed here, but individual detailed descriptions for each fuel will accompany the case studies.

Likewise, energy is also used for a multitude of different uses (so-called "end uses"). These include space and water heating, cooking, lighting (domestic, offices, shops, advertising, street and public lighting), air conditioning, refrigeration, fans, motive power (in industry), and a whole host of other domestic household appliances. Only the weather-sensitive uses will be of interest to us here. In a similar way, these too will be discussed in separate Chapters. Similarly, individual fuel management systems appropriate to each scale will receive detailed attention in the separate case studies. In particular, much more will be said about the problems facing daily electricity and gas forecasting and management in Chapters 5 and 6. The previous two sections were designed to serve only as general introductions to energy management/structure and weather sensitivity.

1.1.6 ENERGY MODELLING RESEARCH AND MODEL TAXONOMY

1.1.6.1 ECONOMICS, CONSERVATION AND ENERGY METEOROLOGY

Energy modelling studies show a notable and unfortunate lack of attention to other meteorological variables besides temperature. Sadly, this also applies to demand forecasting research. Meteorologists themselves have published little relating to the value of weather data for the energy industries. "The meteorology of energy" or "energy meteorology" as a scientific field, is not even formally defined in current research as yet. The present pool of knowledge on energy modelling, naturally enough,
comprises a complex mixture of theoretical and empirical approaches and widely varying methods, though some broad classifications (taxonomy) are possible. Any categorisation of models is subjective, however, and the following are illustrative examples.

Many socio-economic and political factors also influence energy demand. These embrace fuel price variations (step changes and inflation), strikes, bank holidays (e.g. Xmas, Easter), regional block industrial holidays, government conservation policies, international football matches (for TV), and other miscellaneous special events such as Blackpool illuminations (large surge in lighting demand) or the Royal Wedding. It is hence not surprising that many studies have concentrated on the interaction of weather and economics on energy consumption. The task here is to isolate all these variables so as to examine the weather sensitive component.

There is a growing body of opinion amongst energy management circles that energy conservation, in all its aspects, is of foremost importance. Accordingly, fuel conservation is now deeply integrated into Britain’s energy policy. This study could possibly come under this heading too, though the current body of knowledge fails to recognise its potential incorporation into this sphere.

Standard energy research erroneously shows a remarkable detachment from meteorology, and many of the relevant journals concentrate almost exclusively on energy conservation or economics. See the Department of Energy’s monthly journals “Energy Trends” or “Energy Management” for economic aspects and conservation respectively. Any purpose of energy modelling to understand consumer response should ultimately be geared towards demand forecasting. To forecast anything that hasn’t happened yet is very useful, and this is particularly true of power consumption in view of the large financial savings possible.

Regarding energy meteorology, the time scale for which energy demand predictions are required varies from up to two years or more ahead, down to 1/2 hour ahead in the Control Rooms. As examples of the former, long term predictions are
made of winter peak demands under "Average Cold Spell" (ACS) weather conditions for 6 months to 2 years. For medium term planning too, forecast consumption is expressed in terms of standard weather demands such as ACS, "Extreme Severity Peak Demands" (1 in 100 winters) and "Seasonal Normal Weather Demands". Other risk criteria and uncertainty levels are used, all based on probability theory, load duration curves or return periods. They are all probabilistic projection techniques and are based on average weather (i.e. climate) rather than actual weather.

Though here we will be modelling on a range of scales, forecasting will be restricted to short-term (daily). Prediction of annual sales, seasonal normal and ACS demands forms a separate area of work from our point of view. Despite its importance in Operational Research and Corporate Planning departments of the fuel industries, this aspect will not be reviewed here, and very little will be said about medium/long term planning and forecasting hereafter.

Various types of institution have made contributions to energy-weather modelling, such as Central Government (Department of Energy), the fuel industries themselves, and academia (Universities and several other academic/educational establishments). These vary widely in their quality, time scale and style, some are published whilst some are unpublished and inaccessible. Hence many types of model exist, and there is no shortage of both theoretical and empirical research.

1.1.6.2. THE SPECTRUM OF SCALE AND OF MODEL SOPHISTICATION

Energy models vary considerably in their design, complexity and data requirements according to the time and space scale, and their degree of sophistication. Thus a suitable taxonomy or classification might be based on scale or complexity. For example, individual Electricity or Gas Boards predict hourly or daily demands, using weather parameters as independent variables. Such models are deterministic mathematical/statistical models and are normally computerised. They are used to forecast the locus of demand (e.g. the daily load curve) and are usually for
the regional, or even coarser spatial levels of aggregation. Any economic factors normally assume background importance. In most cases, they are written by statisticians or internally by energy personnel. They are in general quite sophisticated and require non-trivial amounts of computing time. These are by far the most useful and financially worthwhile types of model, as they are used on-line in real time applications within the power industries. In them, weather forecasts are very important components in the decision-making process. This is the type of model developed in Chapter 5 for forecasting daily regional electricity and gas demand.

At the other end of the spectrum of statistical complexity and time scale we find the “energy-climate models”. These will be referred to as “econoclimatic models” in keeping with the convention adopted in standard energy literature. They model the interaction of climate, rather than weather, with energy demand on fairly long or very long time scales, say months to years (i.e. inter-seasonal/inter-annual). They incorporate both meteorological and economic/demographic variables and are used to project power system growth for capital expansion requirements. Such medium and long term planning models are generally more econometric in their design characteristics and structure. Geographers and economists tend to adopt this approach. This class of energy-weather models normally applies to a region or a whole nation.

On an intermediate time scale, there are models that analyse demand on monthly or weekly time scales. Chapters 3 and 4 provide examples of models derived on these scales respectively. In the literature, studies on this scale are often oriented to conservation and include a large number of miscellaneous studies from academia, industry and government.

The finest time scale on which energy modelling is possible is hourly (actually half hourly). Improvements in models on this and on the daily time scale are of immense interest to the energy industries. In hourly electricity and gas prediction, attention is concentrated on forecasting
peaks in the demand "locus", i.e. times of maximum demand. These include the breakfast, lunchtime and teatime peaks, as illustrated in Figure 1.1. Figure 1.1 will be referred to later, and it shows loci (time profiles) of hourly electricity and gas demand obtained from South Scotland Electricity Board (SSEB) and Scottish Gas respectively. The day 20 March 1979 was chosen arbitrarily from a much larger hourly data base, as a typical (moderately ordinary) winter-time weekday. A later case study will also include this day. As well as indicating the mealtime peaks (due to cooking, heating and lighting), several other interesting features also show up, which will be of relevance later. Both hourly series show demand to be low during the early hours of the morning. Such overnight loads comprise heavy industrial loads (24-hour continuous process industries) and domestic storage heating. There is a further boost in electricity demand mid-evening (Figure 1.1) due to TV viewing, after which demand gradually falls off as evening activity dies away. There is no detectable supper-time peak.

Energy models could also be classified by space scale. Most of the above are for the regional or national levels of aggregation, but models have also been developed for microscale studies. Most of these are geared towards examining energy efficiency and/or conservation in single homes, flats, offices, schools, etc, or small groups of buildings. Chapter 4 falls into this class of models by investigating energy consumption in two groups of buildings, and is the closest we will get to classical energy conservation as such. Builders, heating engineers and architects have all made very significant and relevent contributions to this area of energy research.

1.1.6.3. SECTOR MODELLING, NORMALISATION AND OTHER TAXONOMIES

Further taxonomic criteria are possible. For example, within the fuel industries, daily demand forecasting models fall into two broad types. On the one hand, there are those that use meteorological data (weather forecasts), i.e. "weather-demand" models. In contrast, there are models using only past demand data (so called "autoregressive" or
Figure 1.1: Time profiles (loci) of hourly S. Scotland Electricity Board (SSEB) and Scottish Gas demands, for Tuesday, 20 March 1979. A = breakfast peak; B = lunchtime peak; C = teatime peak; D = mid-evening peak.
"exponential smoothing" models, see later). Both need large volumes of data, typically tens of years of historical weather and demand information. Their complexity ranges from simple manual schemes to the highly sophisticated Box-Jenkins methods, which are becoming more widely used in energy forecasting applications and which will be described later.

Likewise, classification by sector or by method/purpose is potentially useful. Several studies have concentrated on individual sectors of the energy market, e.g. just domestic space-heating. This is particularly true of American literature, where domestic tends to be called "residential". These will be termed "sector modelling studies". They analyse energy demand by customer category, and are typically for residential housing estates (local-scale) or for the sub-regional scale (i.e. intermediate space scales). Very often, consumption by fuel use is individually metered, and the emphasis is nearly always conservation-oriented.

Many modelling studies have been limited to establishing weather dependencies in order to perform retrospective weather correction of past demands. The purpose of removing the influence of weather on consumption is to look at the effects of other non-weather factors such as economic/political factors, or the impact of energy conservation policies, on trends in energy sales. The process has been frequently referred to as "weather normalisation", "deweighting" or "adjustment" of past energy sales. The concept of normalisation developed from economists' interests in energy trends and Governmental policies. Chapter 3 contains an example case study of this approach.

Atmospheric conditions exert an important control on the transmission and distribution of energy, in addition to demand. That is the weather not only affects the load on the plant but can also injure, or even cause severe damage to, equipment and hence interruption of supply. Several studies have therefore concentrated on this direct aspect of weather sensitivity, and this is especially true of electricity.
Such effects include lightning damage to overhead power lines and pylons, glazing and sleet storms, gales, burst pipes, etc. Energy engineers make use of weather forecasts for planning repair and maintenance schedules of such equipment and other plant.

With such an interesting diversity of approaches, it is clearly important to select those of relevance to this study. We must now, therefore, conduct a thorough survey of relevant previous investigations, to place this contribution in the context of the body of knowledge as a whole, and in its historical context. It is probably fair to make the generalisation that the field has received more attention in American literature, probably because of the greater extremes of heat and cold experienced in that continent. Furthermore, more succinct but rather more specialised literature surveys will be conducted more appropriately as they arise in the context of each case study. In particular, Chapter 2 reviews the relevant statistical literature as the techniques are described. The following account is comprehensive and international, and it is very nearly exhaustive.

1.2. A COMPREHENSIVE REVIEW OF PREVIOUS LITERATURE

1.2.1. THE PRESENT STATE OF KNOWLEDGE

It should be pointed out from the outset that this field has not received the attention it deserves, especially considering the potentially very worthwhile savings. Within the fuel industries, traditional modelling methods have been handed down and retained largely for historical reasons. There is some degree of resistance to change (innovation vs tradition). The research that is carried out is confined to internal papers and confidential Working Party reports. There is a paucity of such work in the main pool of published literature as a whole. It is hoped that this contribution will help to remedy this deficiency.

It is convenient to subdivide previous investigations into "mainstream" (published) research, that is outwith the power industries, and "internal" literature, which is
normally unpublished and difficult to acquire. Both are obviously very important for our purposes. The following represents a general summary of the present pool of knowledge, and is mainly expository. That is, very few statistical methods or equations are introduced at this stage. The account is strictly in chronological order and therefore necessarily comprises a mixture of scales.

1.2.2. MAINSTREAM LITERATURE

1.2.2.1. PRE-1960

The earliest known published reference (to the author's knowledge) to weather-demand analysis was in 1939. Gilkeson (1939) discussed very simply and briefly the use of weather forecasts in electric power operation. Smith (1939) casually examined the use of meteorology in natural gas dispatching. An explicit method of actually forecasting demand using weather data was first reported in 1944, in a paper read before the American Institute of Electrical Engineers, relating to a successful application by the Philadelphia Electric Co. (Barnett, 1972). Later that year a similar linear regression method was instituted in the St. Pauls Grid Control Area (GCA), now Grinstead GCA. Hewson and Longley (1944), in their consideration of meteorology and human activities, include a short section on public utilities and weather effects. The first modelling study to emerge, albeit simple, was made by Dryar (1944), who looked at the effects of several weather variables (temperature, wind, rainfall, sunshine, cloud) on energy usage. He expressed the weather dependence as percentages of raw demand and called these weather weights. These were then used to deweight or weather correct historic energy sales.

In 1945, a joint meeting between the Royal Meteorological Society and the Institute of Electrical Engineers (IEE) looked at the effects of weather on electric power systems. Forrest (1945) summarises the conclusions therefrom. Most attention was given to direct damage of power systems by lightning or riming. Also in 1945 came the first published discovery of the effect of illumination on
lighting demand. Schiller (1945), in an Electrical Research Association report, uncovered this dependence, which was later to be used by other workers. Dryar (1949) made a study of load dispatching and weather in Philadelphia. Brooks (1950) made some simple but nonetheless very interesting comments on heating, lighting and air conditioning, and does include brief comments on weather and energy consumption.

The next contribution came from Lacy (1951) who studied the effects of temperature, sunshine and windspeed on the heating requirements of single family homes and bungalows, using a simple multivariate scheme. Most post-war British studies were either in the vein or style of fuel conservation or were oriented to regional case studies of a particular fuel. In 1953, Williams and Leslie found present and past temperatures and daylight illumination to influence electricity consumption. Fleishman (1954) investigated temperature sensitivity of electricity demand at two sample hours, 0600hr and 0900hr. Few pieces of research have looked at the time variation (hourly, daily, weekly or seasonal) of such sensitivity. Phillips (1956) describes the problem of line sag due to glazing of overhead power cables in the Grampians, and how it can cause breakdown or interruption of supply. Manley (1957) made a simple study of climatic fluctuations and fuel requirement, using monthly temperature data during the heating season.

The classic contribution came from Davis (1958) in an Institute of Electrical Engineers monograph: "The relationship between weather and electricity demand". In it he developed a multivariate model involving past and present temperatures, windchill (a combination of temperature and windspeed) and illumination (as estimated from reports of cloud, visibility and precipitation). His method is still in operational use today for on-line CEGB daily and hourly load forecasting, and his index of "effective illumination" (EI) has become commonplace therein. He was the first to detect the effects of precipitation (actually rainfall rate) and windchill (windchill literature will be reviewed separately later). He should perhaps be regarded as the father of modern energy-weather modellers, and his work is generally
recognised as very valuable and led the way for several other similar studies. It also stimulated interest in other meteorological parameters. Since then the story has been one of gradual computerisation, and associated increases in sophistication of techniques and the introduction of totally automatic operational models.

1.2.2.2. THE 1960’s AND THE ADVENT OF COMPUTERISATION

We now enter the main body of the historical review. The 1960’s brought a revolutionary change in this field, as indeed it did in many other disciplines, due to the rise of computer technology, though there was some continuity carried over from pre-1960 days. This affected academic research, industry (power production) and government alike, and models as a result became more advanced. In the fuel industries, energy models began to assume a more automated nature, and partly replaced traditional manual methods. In research at Universities and other academic establishments, more time-consuming (in computer terms) sensitivity experiments in energy modelling became possible. This transition phase serves to provide a convenient discontinuity in this historical treatment. The result was a string of energy modelling publications and sensitivity studies involving several meteorological parameters.

Davies (1960) comments on the (rapidly becoming computerised) operation of the National Grid using weather forecasts, and quotes examples of sensitivity of demand to various meteorological variables. Davies’s study is not primarily one of demand prediction, but rather one of modelling the effects of wind, cloud, fog and precipitation. Harris (1964) found temperature and relative humidity to be important controls on electric power usage at peak periods in New Zealand. Rapp and Huschke (1964) discussed the use of meteorological information for the energy industries. Nye (1965) made a detailed study of weather effects on the electricity industry. He considered the economic value of services provided by the Australian Bureau of Meteorology for predicting electricity consumption.

McQuigg and Thompson (1966) assessed the financial
value of improved methods of translating meteorological information into operational terms for computerised prediction of gas consumption. They were considering the flow of natural gas through the distribution system of a company serving Columbia, Missouri. They demonstrate that "average annual loss functions" are dependent on the standard deviation of forecast temperatures. Mason (1966) assessed the economic value of meteorological services and weather forecasts to the national economy, including the energy industries. Critchfield (1966) summarises the direct effects of the weather on power lines, and the problems facing cables due to riming and strong winds. He emphasised the importance of anticipating future gas demands in severe weather.

Matthewman and Nicholson (1968) describe a computerised technique for electricity load prediction (actually Davis's method) using temperature, windchill and cloudiness. They discuss various other techniques for electric load prediction and the problems concerned with load flow analysis, and use an application of eigenvector analysis as one variation. Richard (1968), in a paper on environmental effects on the heating and air conditioning industries, indicates (rather vaguely) that the U.S heating industry is now working on a total energy computer programme. WMO (1968), in a report on economic benefits of National Meteorological Services, assess annual financial savings realised by the energy industries of France, W. Germany and Australia, by using weather forecasts.

Johnson et al (1969) related peak hourly electric air conditioning loads to daily temperatures for Summer 1966, using standard regression techniques, for 14 large utility companies (power systems) in the American Mid-West. As an example, a positive correlation (due to space cooling) of 94% was found for Iowa and Illinois Gas and Electric Co., and Kansas City Light and Power Company.

Rouvel (1969), in a German paper, established a linear relation between heat requirement of an all-electric housing estate with meteorological conditions.
2.3. POST-1970 AND HEATING/COOLING DEGREE DAYS

Another suitable discontinuity in this historical treatment is provided by the widespread introduction of degree days as a method of weather-demand analysis. This technique became popular throughout the 1970's, in industry, government and research, and is still widely used in American literature today. "Heating degree days" (HDD) can be defined by:

\[ \text{HDD} = \sum (T_{\text{COMF}} - T); \text{ when } T < T_{\text{COMF}} = 0 \text{; otherwise} \quad (1.1) \]

where the summation is over number of days (say 1 month).

Here, \( T \) is daily mean temperature and \( T_{\text{COMF}} \) is a subjectively defined "comfort temperature". This is the author's term for what has been variously referred to as "base", "reference" or "threshold" temperature in the literature. It is the critical temperature above which heating load is assumed to vanish. 18 deg C is the presently accepted value in this country, and its adequacy has been fully documented.

HDD is the total accumulated number of degree differences between actual and base temperature, calculated only when \( T < T_{\text{COMF}} \), and only during the heating season. When \( T > T_{\text{COMF}} \) there is no contribution to the total degree days. Heating degree days can thus be visualised as a measure of accumulated cold. Interestingly, the thermal life of some temperate plants and grasses is governed by such measures of past coldness (in that case below, say, 6 deg C).

Degree days are useful in investigating heat requirements of buildings, and have been used widely by energy personnel, heating engineers and conservationists. Monthly degree day statistics are published by the Department of Energy in, for example, Energy Management, for various regions. They are often correlated with energy consumption, and can be a useful guide to temperature dependence. The rationale behind the method is that when \( T < T_{\text{COMF}} \), some heat is used, and the amount used is proportional to the amount \( T \) falls short of \( T_{\text{COMF}} \). In this country it is perfectly reasonable to assume negligible
heating load above 18 deg C (shown later), but in hot climates the air conditioning/ refrigeration load is very significant. In such circumstances, "cooling degree days" (CDD), for space cooling load, can be computed in a similar but reversed manner.

There are various inherent problems in the approach which are not always explicitly recognised in their application, not least of which is that of choosing a realistic national average TCOMF, and the restriction of its use to coarse time scales. Degree days can give misleading results for daily or weekly data, and are not a reliable indication of fuel consumption in those circumstances. "Degree hours", the counterpart of degree days on the daily time scale, have been suggested from time to time in the literature, but have not come into general use. It was felt here, as a consequence of these drawbacks, that the degree days approach is not productive or reliable with fine time scale data, but is more suited to coarser scales, e.g. monthly/seasonal.

Nevertheless, the approach has formed a very important part of previous energy modelling studies, and these studies are of considerable relevance and interest to this work. They must therefore be briefly reviewed, in parallel with other methods used since 1970. The literature is full of interesting variations of the method and its applications to many energy-related problems.

Maunder (1970), in a comprehensive evaluation of the value of the weather for all weather-sensitive enterprises, used degree days to consider the effect of temperature variations on retail sales of house heating oil in Canada. He reports that data supplied to students by fuel oil dealers in Victoria, British Columbia, were used to correlate degree days with oil consumption in oil-heated homes. He also quotes that several gas companies have found it profitable to employ consultant meteorologists, who can interpret weather conditions specifically in terms of the problems of gas distribution. Christiaanse (1971) used general exponential smoothing (i.e. past load data only, see Chapter 2), for short-term electricity forecasting.
Maunder (1971) looked at the value and use of weather information for New Zealand electricity generation. Also for New Zealand, Maunder (1972a and b) established national energy-climate models, in the first instance for the New Zealand Meteorological Service, in the second for the New Zealand Geographer.

Taylor (1972), in a volume entitled "Weather Forecasting for Agriculture and Industry", forms a useful collection of papers on economic benefits of meteorological information for several sectors of the economy. Of special interest therein is the paper by Barnett (1972), on weather and short term electricity demand prediction. Of the many general sensitivity studies available, this is possibly the most interesting. He quotes typical winter temperature sensitivities of CEGB electricity demand. He was one of the few to bring out the influence of rainfall, and makes the point that sensitivity has a diurnal as well as a seasonal pattern. Gupta and Yamada (1972) use weather information for short term (hourly) predictions of electricity consumption.

McQuigg (1972) prepared a paper for a WMO Panel on Meteorology and Economic and Social Development, in which he examined the use of meteorological information in economic development, including energy forecasting. McQuigg et al (1972) estimate diversity of electric power load from variability in temperature using matrix theory and eigenvector analysis.

Ludlum (1973) published a short article on the use of degree days in studying trends in U.S fuel consumption. Oliver (1973), in a volume on climate and man's environment, extended the concept of degree days and introduced "freezing degree days" (degree days that are -ve when T<0 deg C, i.e. base temperature is 0 deg C), and "thawing degree days" (otherwise). He also reproduced a NOAA map of U.S annual heating degree days. Clayton et al (1973) describe a weather-sensitive electricity load model. Corpening et al (1973) review their experience with weather-sensitive electricity demand models.

Mitchell et al (1974) made a general but useful study on the variability of seasonal total fuel demand in the
The natural gas and electricity industries of the United States are rather more susceptible to the weather than ours, being subject to much more extreme conditions of heat and cold (continental vs maritime climate). This explains the greater American interest in weather-sensitive power consumption.

Taylor (1974) brings together several interesting studies in a volume named "Climatic Resources and Economic Activity". For example, the paper by Maunder (1974) therein looked at national econo-climatic models. He researched the dependence of monthly electricity generation in New Zealand on monthly temperature departures from the 1931-60 normal.

Ryan (1974) incorporates degree days into a weather dependence model of gas demand in Virginia. His paper appeared in an American Gas Association publication, and also involved other aspects of gas sendout forecasting with weather-sensitive loads. His other chosen independent variables included windspeed, cloudiness and average snow cover. McQuigg (1975) warns that long-term projections using energy-temperature relations are risky. Bhattacharyya et al (1975), in a NASA report, made assessments of the annual value of weather forecasts to the U.S fuel industries.

Further sector modelling studies followed, some using degree days, motivated by the increasing interests in energy conservation. The first in this spate of studies was Durrer and Somerton (1976), who correlated gas demand for residential space heating with meteorological data. Reiter et al (1976) discuss generally the effects of atmospheric variables on energy efficiency in homes and buildings. Thompson (1976) details a scheme for analysing weather-sensitive hourly electric loads on the Pacific Gas and Electric Co., California, including space cooling loads.

Mayer and Benjamini (1977) produced a piece of work correlating monthly degree days with residential natural gas consumption. Monthly demands were then temperature-adjusted to evaluate the impact of energy conservation policies. Davis (1977) produced an influential report on energy and climate, and stresses the general widespread need for energy meteorology research. Kane and Brownfield (1977) derive a


The Department of Energy (1979), in a fuel efficiency booklet, summarise the main points for and against using degree days. HMSO (1979) publish a valuable general pamphlet on the current state of the energy industry ("British Industry Today: Energy"). Though not strictly meteorological, it does form useful and interesting background reading on all the power industries. Central Government (Department of Energy) also publish many reference pamphlets and white paper offprints. In addition, Annual Reports and Statistics are available from CEGB, Electricity Council, British Gas and NCB. See also Digest of United Kingdom Energy Statistics (DUKES, published annually) for comprehensive annual statistics on all energy forms.

Returning to meteorology, Clark (1979) carried out some research on gas demand in severe weather, as relating to N. Thames Gas Board. His scatterplot of daily temperature vs demand is reproduced in Figure 1.2a. Over normal U.K winter temperature ranges (say 0-15 deg C), the dependence is almost linear. Down to the lowest temperatures, Figure 1.2a displays no visual evidence of demand saturation (decreasing sensitivity at very low temperatures). The interesting thing about his curve is that it does show evidence of decreasing sensitivity at temperatures above about 18 deg C, i.e. some tailing off of the curve. We would after all expect this to happen when T gets above TCOMF.

Lyness and Whitting (1979), of British Gas HQ, looked at forecasting and planning aspects of gas usage in severe weather. Guayle and Diaz (1980) regressed heating degree
Figure 1.2: a) Scatterplot of daily N. Thames Gas demand vs temperature (after Clark, 1979)

b) Daily peak electric load vs temperature for an American company with both space-heating and cooling loads (after Warren and Leduc, 1981).

Neither author quotes how curves obtained (whether "best-fit" in least-squares sense)
days on residential heating oil and electric power consumption for 40,000 dwellings in N. Carolina over 11 years. They hint at the usefulness of accurate temperature projections for energy forecasting. Proctor (1980) used degree days to investigate the general impact of weather on electricity demand. Grieg (1980) investigated the weather sensitivity of water demand by the electric power industry. Takenawa et al (1980) detail a computer program for predicting total system loads on electric power utilities.

One particularly instructive study is that of Warren and Leduc (1981). They use a technique based on the linear relation between heating degree days and natural gas consumption for space heating, to quantify the interaction of climate and prices on monthly and seasonal energy demand. The scatterplot they obtained for daily temperature vs load for an American electric utility is presented in Figure 1.2b. If we ignore the strange intervals on the axes scales, then this is a very interesting plot for comparison with Clark's plot in Figure 1.2a, but the reader should note temperature axes are in the opposite sense. Over normal (for Britain, 0-15 deg C) temperature ranges, the relation is strongly linear (as in Clark’s curve for England), and there is some evidence of demand saturation at very low temperatures (<-20 deg C). The second interesting difference between this and Clark’s curve is the rapidly 'increasing' sensitivity above TCOMF. In the plot of Warren and Leduc (1981), Figure 1.2b, loads at >25 deg C are considerably higher than those at very low T. This important difference is due to the air conditioning/refrigeration load (fans and space—cooling plant) which is very significant in the U.S. It is difficult to make any other sensitivity comparisons between daily gas sendout and peak electricity load.

Figure 1.2 has thus served to bring out a fundamental discrepancy between British and American energy sensitivity to temperature, and as such both plots will be of relevance later, and will prove useful on several occasions. The existence of large space—cooling loads in the U.S.A. has, as we have already seen, led to a quite different emphasis in the literature. Relative humidity is also frequently used in
American studies due to the large air conditioning/ space cooling loads, e.g. in the hot and humid S.E. States during summer heat waves.

As an example, Comte and Warren (1981) use national weekly cooling degree days (population-weighted) to model the effects of summer temperatures on U.S electricity consumption, during the cooling season only. They use data provided by Edison Electric Institute (EEI) for the entire 48 contiguous States during the cooling season, see also EEI (1978). According to Lighton (1981) the use of meteorological forecasts has allowed better management of gas storage capacity and supply co-ordination. ASHRAE (1981), the American Society of Heating, Refrigerating and Air Conditioning Engineers, related degree days data to residential heating fuel consumption.

The U.S. National Climatic Center (1981a). or NCC, examined standard deviations of heating and cooling degree days in the U.S. NCC (1981b) published state, regional and national monthly and seasonal heating degree days, weighted by population. Forecasts of gas demand are routinely published by NOAA's Center for Environment Assessment Services, throughout the American heating season. Proctor (1981) assessed the economic impact of climate for the gas and electric utility industries. His paper, for the Oklahoma Climatological Society, presented methods of weather-adjusting utility load curves, see also Viren (1981).

Browning (1982) edited a volume titled "Nowcasting" in which a paper by Murphy and Brown of Oregon State University appeared. Murphy and Brown (1982) consider the user requirements of very short range weather forecasts for agriculture, transport, public safety and industry (including energy). They provide a short summary of annual economic value of meteorological data for the energy industries in several countries, and the use of weather information to the community. Greig (1982) reported the importance of seasonal climate forecasts in water management for steam-electric generation.

Winterburn (1982), in a paper delivered to a Royal Meteorological Society Conference at Imperial College,
London, stressed the impact of freezing rain and icing on electric power supply systems. Morris (1982) conducted a study of the accuracy of temperature forecasts for the British gas industry. Bolzern et al. (1982) describe the relation between daily temperature and winter electricity load on a power grid in Italy. Weiss (1982) makes some interesting points concerning the usefulness of seasonal climate forecasts in managing energy resources. Andrews (1982) wrote a short note emphasising how an American gas utility benefited from improved and extended (in lead-time) weather forecasts, and how very significant monetary savings were thereby realised by ratepayers of the Washington Gas Light Co.

To the author's knowledge, the most recent study is that of Guttman (1983). He examined the variability of seasonal heating degree days over the entire 48 conterminous United States, and claims to partially update the study of Mitchell et al. (1974). Palutikof (1983) wrote a paper on the impact of weather and climate on U.K. industrial production, including power output. He demonstrates how seasonal weather extremes, such as severe winters or droughts, affect industrial output and the electricity/gas industries.

1.2.3. INTERNAL LITERATURE

Now that the mainstream wealth of published literature has been adequately covered, we must now undertake a review of unpublished research available within the fuel industries. This material to be reviewed is almost exclusively British. The author is not at present in possession of any foreign internal energy research, though some studies cited elsewhere will be quoted here. Despite its general unavailability, this internal work does form a very significant force in energy research specifically and in energy R and D programmes generally. Since it is at the frontiers of such research, it is the most progressive of all energy meteorology literature.

Internal literature takes the form of research papers, Working Party reports and various other internal notes, files and memoranda. There is a much smaller quantity of
this type of literature, mainly due to restrictions on its access. Being private communications, the information is not strictly available to the general public, and there are various other restrictions relating to copyright and confidentiality. Hence the review is of necessity not comprehensive. A similar but even more stringent restriction problem applies to acquiring demand data (e.g. hourly series in Figure 1.1, see also later in the thesis). Most of the internal papers have been collected from personal visits and some are available from the respective author.

The forthcoming account is once again strictly chronological, and cross references will, where appropriate, be made to personal communication to support the comments. Most contributions have emerged from Central Government (Department of Energy), British Gas HQ, Electricity Council, CEBG, and Area Electricity and Gas Boards (mostly Operational Research and Corporate Planning departments). Contributions have also been made by architects, heating and lighting engineers and other bodies such as the Building Research Establishment (BRE) at Watford. They tend to be rather more physically-based than mainstream studies. It is probably fair to say, as a generalisation, that apart from some aggregate regional energy modelling and forecasting feasibility studies, there is an absence of sector modelling studies, unlike the mainstream (mainly American) literature. This is partly due to the lack of data on sectoral breakdown of demand in this country. There is, on the other hand, a notable abundance of interesting local microscale studies on private domestic dwellings, weather and architecture, interior microclimate, housing and ventilation studies and, of course, energy conservation.

The Egerton Report (1945) emphasised the need for major research into problems of domestic heating and ventilation. The report encouraged many post war energy-weather studies, and stimulated BRE to turn their attention to this problem. Rose (1949) gave a famous paper to the Institution of Gas Engineers (IGE) in which he appears to be the first to identify the nature and scale of gas demand response to temperature. It should be credited as a valuable
piece of research and, so far as the author is aware, he was the first to detect a lag in consumer response to temperature. He was using 1938 data from the Gas Light and Coke Co., and gave evidence of increasing sensitivity of daily gas demand at very low temperatures. He pioneered this and other aspects of energy meteorology in the British gas industry. As a legacy, his linear demand-temperature model is still in use today in N. Thames Gas Board.

The interest in weather effects on domestic heating and ventilation continued until the early 1960's, when BRE's interests were directed more towards heating in offices and schools. The British gas and electric industries actively produced domestic heating studies through the 1960's and 70's. Most studies carefully selected housing samples and looked at local weather effects. Only rarely did national studies emerge during this phase of energy research.

The United Nations (1962) looked at short term meteorological influences on electric power demand. They quote that even in Cyprus (with load around 70 MW) winter demand is equally affected by sudden temperature falls and changes in light intensity. Black and Milroy (1964) made studies of space and water heating in local authority flats, see also Dick (1961). Baker and Davis (1965), in a CEGB Operations Department note, detail some interesting and useful specifications of routines for processing of weather data ready for demand projection.

Heinemann et al (1966), at an IEEE Power Meeting in New York, found summer electric loads to be sensitive to actual and lagged temperature and to windspeed. Badger and Lyness (1969) made a valuable national study of the relative severity of past winters as regards gas storage.

In Sweden, Petersen and Gothe (1972), at a Symposium on electric supply, found solar radiation intensity, temperature, cloudiness, wind and visibility to affect national electricity consumption. In the proceedings of an IGE Research Meeting, Turton and Harper (1973) evaluate the role of weather forecasts in short term predictions of gas demand.

A variety of internal research papers have arisen out
of the Electricity Council during the 1970’s. Many of these concentrated on weather correction or deweighting of unit (KWh) sales, such as Burchnall (1973) in an internal memorandum, Fletcher and Bates (1974). Bain (1975), of CEGB Management Services, prepared a document detailing a program for processing historic weather-demand data. Boggis (1975) examined the dependence of electricity demand on temperature and lighting, using daily data from three winters. The most notable and readable of this series of studies, and the most relevant here, is the system of weather correction known internally, and somewhat colloquially so, as "METVAL", proposed by Bates and Bridge (1976) in the EC Internal Paper EF75. They illustrate the use of temperature (actual and lagged), windchill and Davis’s index of effective illumination (EI) for retrospective weather normalisation of past unit sales.

Internal Governmental papers of the Department of Energy (Economics and Statistics Division) quantified the temperature dependence of monthly coal and oil consumption. The author is not aware of any other British or American literature that performs such for coal or oil on anything deeper than a casual descriptive basis. Department of Energy (1976) used a Box–Jenkins type analysis on 6 years of national monthly temperature and industrial coal demand data. The Department of Energy also has an Energy Technology Support Unit (ETSU) at Harwell, Oxfordshire. This body advises on various issues of R and D policy, energy conservation, alternative sources of energy and produces various publications on energy research.

Humphreys (1976), in a BRE Current Paper (BRE CP 75/76), investigated desirable temperatures in dwellings. He has also made several other contributions to understanding human thermal comfort in relation to interior and exterior temperatures and internal microclimate, notably Humphreys (1974). Other biometeorology studies involving human comfort in relation to temperature, humidity and wind, etc, will be referred to in a later Chapter. A substantial Working Party report also came out of the Building Research Establishment in 1975 (BRE CP 56/75). This was a comprehensive study of
energy consumption in buildings in which several references are made to weather. It considered ventilation and heat loss, space- and water-heating and lighting in housing, and almost inevitably conservation. Department of Energy (1977) produced a Working Party report on temperature dependence of national oil and coal consumption, again for the U.K.

BRE also print internally some interesting news leaflets and small booklets on energy—weather research on buildings. Such is BRE News 34, in which Courtney (1976) considers district heating schemes. Leach (1976) looks at fuel savings in homes, offices and schools as well as ventilation studies and their need for meteorological data. In the same volume, Crisp (1976) studied lighting demand in schools and offices, and he includes hourly lighting load curves (and is unique in doing so). The ventilation work of Warren (1976) monitored windspeed and temperatures (internal and external).

Licence (1976), in an IGE communication delivered at an AGM, outlined weather—related aspects of strategic planning in the gas industry. Baker (1977), in a paper presented before a Public Utilities Forecasting Conference in Windermere, describes daily and hourly CEOB demand forecasting, and details the computer systems used.

The late 1970's witnessed an increasing interest and active involvement (relatively) of the British gas industry in energy meteorology research, especially following the severe winter of 1979. The work of Lyness, of British Gas HQ, very much paved the way in this field, and inspired a string of related papers. For example, Taylor and Lyness (1978) assess the applications of temperature—demand techniques to long term planning. On the contrary, there was a gap in electricity contributions.

Operational Research departmental report, evaluated several regional temperature-demand models. Lyness (1980, personal communication) confirms these to be widely varying. Piggott (1980) of the R and D division of BGC, presented a paper to the Royal Statistical Society in London. In it he outlines the use of a Box-Jenkins technique for forecasting daily gas demand using temperature and windspeed. Jenkins and Taylor (1980) of British Gas HQ Operational Research Dept, provide a review collating regional short-term gas forecasting procedures. This document (Internal Paper F80/11) illustrates the wide variety of methods between regions. Leach (1981) provides various useful energy related statistics for British domestic dwellings, and hints at the importance of weather effects.

Bruce (1982), in a paper read before a Wind Symposium at Edinburgh University, discussed the effect of wind on heat loss from buildings, and the resulting influences on energy consumption. The Electricity Council (1983) and British Gas HQ (1983), both private communication, insist on the need for further work on all these aspects, especially the effects of variables other than temperature, such as windspeed (for ventilation-induced heat loss), solar radiation/sunshine and rainfall.

It has thus long been recognised that energy demand on many time and space scales is highly sensitive to the weather. This is supported by international experience and many British and American studies, as we have seen in the foregoing comprehensive review of mainstream and internal literature. There is no shortage of studies recognising the immense importance of weather effects. We must now tackle the statistical theory of energy modelling and the statistical analysis of meteorological and energy data. We can then move on to use these techniques in the modelling and forecasting case studies on various spatial and temporal scales.
CHAPTER 2
STATISTICAL THEORY OF MULTIPLE TIME SERIES ANALYSIS

2.1. INTRODUCTION AND PURPOSE

This Chapter is intended to provide the necessary theoretical background for the later modelling and forecasting case studies. Energy and meteorological statistics are just one branch of a very broad and extremely useful field, hence the treatment is of necessity not exhaustive. As we shall discover, weather and energy data possess unique and interesting statistical properties. Because such qualities are peculiar to them, the study of such data justifies its separation or divorce from the mainstream wealth of statistical theory, to some extent. It also permits the use of several specialised approaches that also are peculiar to this field. That is not to say there is no common ground at all with traditional statistics. There is also a lot of inter-disciplinary overlap with other sciences.

This part of the work forms a useful collection or summary of many techniques, some novel, some standard, some harsh and powerful and some with recognised inherent weaknesses. Where applicable, cross references will be made to disciplines which have applications. Most of the statistical methods to be covered can be, and are, (to varying extents) used in a large variety of fields. These include geophysics, oceanography, operational research, engineering, astronomy, economics and geography, for industry, research and teaching.

The present work represents a mixture of standard techniques and original methods derived here specially for energy meteorology applications. The armour of techniques to be applied is rather varied. Not all of the methods discussed in this Chapter will be used at every stage in the analysis, or for every case study. Some of them have their most useful applications in daily data, and therefore do not appear until then. Similarly, some techniques will not be described until a particular case study, to which they may
be unique. It should additionally be pointed out here, contrary to several authors, that the statistical approach is not dangerous provided one is constantly aware of the variety of potential pitfalls embedded in the theory, and to be aware of physical meaning.

The Chapter has the additional purpose of setting out various definitions to be used, and clearing up several ambiguities and misconceptions regarding semantics. The reader may also wish to refer back to the reference list of variables at the start of the thesis. Sources of error in the data (inaccuracies, uncertainties, etc), and data representativeness in general, will be dealt with in individual Chapters, as appropriate to that particular data base. Defects and merits of each method will be discussed and illustrated separately.

The relevant statistical literature will also be discussed here. It is only a summary; the reader is referred to standard traditional statistics texts such as Kendall (1973), Spiegel (1972) or Findley (1978) for further rigour and amplification. Likewise, the reader is referred to the relevant statistical periodicals for other applications, such as the Journal of Time Series Analysis or Journal of the Royal Statistical Society. Texts on meteorological statistics are few, but see Essenwanger (1976), Brooks and Carruthers (1953) or Panofsky and Brier (1958). None have emerged on treatment of energy statistics. This Chapter forms a significant part of the overall contribution, for it attempts to put on a firm statistical and physical basis some often neglected aspects of statistical analysis of energy and weather data.

2.2. A PRELIMINARY EXAMPLE OF AN ENERGY SERIES

2.2.1. GENERAL CHARACTERISTICS OF ENERGY DATA

We begin our treatment of the statistical framework by considering a single introductory example of an energy series. This daily electricity locus will provide the reader with a convenient and useful introduction to basic ideas and modelling concepts. It also supplies us with a suitable
illustration as we progress through the statistical background. We will not consider in detail this particular data base, since it is only required for illustrative purposes (like the hourly gas and electricity series in Chapter 1). In the case studies themselves, detailed attention will be given to the data. The following is only a summary, therefore, of the basic characteristics of energy data in general.

To relieve repetitiveness, the terms "series", "record", and "trace" will be used to refer to "time series". These words will be used interchangeably. A time series is a collection of observations made sequentially in time, in our case at discrete, regularly spaced times.

Figure 2.1 shows the daily electricity demand for S.E. Electricity Board for 1977 (365 days). A synchronous daily temperature trace for Gatwick is also presented. The first and most obvious point of interest to note is the annual cycle in demand, driven by that in temperature. The sine waves fitted to these data are their first wavenumber as a representation of seasonality, and will be discussed later. Secondly, we can pick out weekly cycles in demand, due to industrial load being lower at weekends. This can be visualised as a weather insensitive base load. If we had several years of such data, we would also notice a long term trend in demand. Figure 2.1 also exhibits several other interesting features. Bank holidays and strikes are special events that must be dealt with by various statistically "legal" adjustments. There is also variability on the time scale of several days or even weeks, due to cold/warm spells. These sometimes mask the underlying short term (inter daily) response. One should also be aware of the multitude of non-meteorological influences mentioned in Chapter 1 (see also Appendix 1). As we shall discover throughout the work, there are many such influences on energy usage, which we will endeavour to uncover.

Without the variability of the atmosphere to cope with, demand prediction would be relatively straightforward. The load curve would then exhibit a semi predictable pattern of daily, weekly and annual variation, together with a long
Figure 2.1: The raw electricity demand (S.E. England) and temperature (Gatwick) series for 1977, with their wavenumber one.
term trend. In nature, the real world is much more complex. This quasi-deterministic systematic behaviour is very much disguised by the apparently erratic behaviour of the atmosphere. This day to day variation in the weather, together with the seasonal variation, accounts for almost all of the variability in demand.

2.2.2. THE TEMPORAL DECOMPOSITION THEORY

To help us to understand (and eventually to predict) the response of demand to weather, it is very useful and instructive to think of the time series as being made up of several distinct, non-interacting components. These appear to behave separately on various time scales, but always add up so as to reconstruct the original raw data. A series can therefore be broken down or decomposed into these constituents, to see which ones explain most of the variance.

It is perhaps helpful to imagine, by analogy, a time series as a point moving with the passage of time, under the action of physical forces (i.e. "locus"). These forces occur on different time scales and are quite distinct. They can be thought of as physically quite separate forces. More commonly they are not quite independent. They may interact; for example, trend and seasonality may be tangled, the seasonal effect may itself possess a trend, or the amplitude of the weekly cycles may vary with season. Even though conceptually they are distinct, their interaction can be a problem. For fundamental understanding of our series, our whole decomposition theory rests on the supposition that each component is due to a different set of forces or causes. We are imposing a model on the situation, but cannot proceed any further unless we do so. Fortunately, the relative magnitudes of such interaction effects are negligible in relation to the components themselves.

The annual and weekly periodicities are to some extent deterministic and predictable. They are so important that large sections of the thesis are devoted entirely to them. Since these components are an average effect that we understand, they may be separated out and removed. What's
left is the irregular, apparently random and noisy component, which varies noticeably on a short term (daily) basis. Its seemingly erratic variability (i.e. stochastic) arises from its weather dependence. By statistical analysis of these so-called "residuals" or "irregulars", we can predict tomorrow's residual demand if we know tomorrow's temperature. This can then be added back to the systematic seasonals and weeklies to produce a total demand forecast.

It is, in fact, a lot more complex than this. Suffice it to say at this stage that such a decomposition philosophy is extremely valuable for us, since the isolation and removal of separate components encourages attachment of physical meaning to each of them. A combination of an additive and multiplicative decomposition will be derived in this work and will be justified later. This ensures the reproducibility of the original data.

More often than not, one is trying to disentangle periodicity, or see order, against a noisy background. Any systematic effects are quite often masked by non-weather effects, or disguised by other meteorological controls on different time or space scales. All of these important points will be elaborated on later in considerable detail.

2.3. LINEAR CROSS CORRELATION ANALYSIS

2.3.1. MATHEMATICAL BASIS

The first and simplest thing we should do, to test the hypothesis that demand is affected by (say) temperature, is to cross correlate them. The strength of linear association would tell us of the usefulness of temperature in predicting demand.

The method adopted here uses "Pearson's Product Moment correlation coefficient" (r), where r is given by:

\[ r = \frac{\sum (X(i) - \bar{X}) \cdot (Y(i) - \bar{Y})}{\sqrt{\sum (X(i) - \bar{X})^2 \cdot \sum (Y(i) - \bar{Y})^2}} \tag{2.1} \]

where: \( \bar{X}, \bar{Y} \) are time means; \( i \) is point in series; and the summations are over \( 1 \) to \( N \) (\( N \) is sample size).
This is a measure of how well a straight line explains the relationship between two variables; or, more strictly, how well the variation in Y is explained by the variation in X. It will be much used and will be referred to as the "linear cross correlation coefficient" ($r$). A value of $r$ close to zero means there is little "linear" dependence, though there could still be some "non-linear" correlation present.

Similarly, $r^2$ (the "coefficient of determination") represents the percentage variance of Y (in this case demand) explained by X (temperature). We quote this without proof. This useful statistic will be used repeatedly. Clearly, one wishes to maximise the ratio of explained variation to unexplained variation.

A statistic that will also be much used is the standard deviation (Sigma), which is the root mean square (rms) deviation from the mean:

$$\text{Sigma} = \sqrt{\frac{\sum(X-\bar{X})^2}{N-1}}$$  \hspace{1cm} (2.2)

This reflects the spread or dispersion of data about the mean. From this definition, equation (2.1) may be rewritten as:

$$r = \frac{\text{Cov}(X,Y)}{\text{Sigma}(X) \cdot \text{Sigma}(Y)}$$  \hspace{1cm} (2.3)

where Cov$(X,Y)$ is the covariance of X and Y.

In the simplest sense, cross correlation of demand and temperature would yield the following linear regression equation, with obvious notation:

$$\text{Dem} = a + b \times \text{Temp} + \text{error}$$  \hspace{1cm} (2.4)

or

$$\hat{\text{Dem}} = a + b \times \text{Temp}$$

where: $a$ is intercept; $b$ is slope parameter (MWh/deg C); error is "Residual error", RE and "\hat{\text{}}" refers to "estimated value".

We shall adopt the first convention of using RE.
This relation represents the least squares regression line through the data, i.e. that which minimises the sum of squared deviations from the mean. Applying this to the electricity data we have:

\[ \text{Dem} = 59281 - 2361 \times \text{Temp} \quad \text{---(2.5)} \]

\[ r = -0.86 \quad r^2 = 74\% \]

The slope parameter, \( b \), tells us that there is a rise in demand of 2361 MWh for every 1 deg C temperature fall, on average, i.e. it is a temperature sensitivity coefficient. That is, it tells us something about the overall sensitivity of demand to temperature. For this simple introductory example, 74\% of the variance in demand is explained by temperature. At first sight, this seems very encouraging. We cannot take these results on face value, as we now show.

2.3.2. SIGNIFICANCE TESTING AND PHYSICAL INTERPRETATION

Before such results are used, one must test their statistical significance and attempt a physical interpretation of them. These should always be done, and this rule will be adhered to throughout the analysis.

We assume for the moment that in equation (2.1) the \( N \) values of \( X(i) \), \( Y(i) \) can be considered as providing \( N \) independent samples of random variables \( X \) and \( Y \), which are both normally distributed about their population means.

The significance of \( r \) can be tested using the \( t \)-statistic, where:

\[ t = \frac{r \sqrt{N-2}}{\sqrt{1-r^2}} \quad \text{---(2.6)} \]

where \( N \) is sample size (=365 here)

The significance may then be evaluated from \( t \)-tables, \( t \) having \( (N-2) \) degrees of freedom. For the daily electricity data, \( t \) is 31.8, and with \( (N-2) = 363 \) degrees of freedom, this would appear to be highly significant (at >99\% level).
Similarly, the significance of differences between two r values, drawn from samples of size N1 and N2, can be tested using the test statistic, Z,

\[ Z = \frac{z_1 - z_2}{\sqrt{\frac{1}{(N_1-3)} + \frac{1}{(N_2-3)}}} \]

where: Z is "Fisher's Z transformation", and z is \( 1.151 \log\left(\frac{1+r}{1-r}\right) \)

The Z statistic has a normal distribution and its significance may be judged from normal probability tables. It will most commonly be used to test whether an "improvement" in r is significant.

Another useful statistic to be encountered is the "standard error of estimate" (SEE), which is a measure of the scatter about the regression line (i.e. the goodness of fit). It is given by:

\[ \text{SEE} = \sqrt{\frac{\sum (Y(a) - Y(p))^2}{N}} \]

where: Y(a) and Y(p) are actual and predicted demand and the summation is over the number of data points.

The quantity inside the square root is called the "error variance". The SEE is clearly the rms residual error. It is a requirement of regression theory that these errors are normally distributed. How this is tested will be described in the following section. A further condition is that the residual errors are independent of each other. This too will be considered in a later section.

SEE has a further application in that it is used in constructing 95% confidence bands for b. The standard error (standard deviation of the sampling distribution of b) is given by:

\[ \text{SE}(b) = \text{SEE} / \left(\sigma(X)\sqrt{(N-2)}\right) \]

Like the mean, r, or any other statistic, the 95% confidence bands for the regression coefficient, b, are as follows:

* if the variance explained is to be maximised.
\[ \hat{b} = b \pm 1.96 \times \text{SE}(b) \]

where "\(\pm\)" refers to "estimate of population value".

That means we can be 95% certain that the real (population) \(b\) lies within \(\pm 1.96 \times \text{SE}(b)\). The confidence bands for other parameters, such as \(r\), are not given here to save space, even though use will be made of them. "Probable error" has now become obsolete in preference to this "standard error", and will not be discussed. There are many other tests we could perform here. Further statistics will be described as they arise in the context of their application. This represents a summary of those to be most frequently used.

A correlation coefficient is simply a mathematical measure of the degree of association between two variables. As such it has no physical meaning in itself. A high correlation cannot be used alone as proof of a causal mechanism linking the variables. Physical interpretation of it can be dangerous as a result. A high \(r\) value does not necessarily imply a real, cause-effect relation, unless supported by strong physical reasoning. Great care should, and will, be exercised in not mistaking "apparent" correlations for real genetic ones of process-response. Spurious correlations may result from things like small sample size or biased (unrepresentative) data.

When working with meteorological or energy data, the fallacy of a "nonsense" or "apparent" correlation is often quite subtle (these are sometimes referred to as "accidental" correlations in the literature). Quite frequently, high \(r\)'s can arise because both variables may be changing in response to a third variable. We will say more about this in Section 2.8.2, in relation to multicollinearity and partial correlation.

In cross correlation analysis, both series may have marked trends or cyclical behaviour, and high correlations may result purely from this. This is rather common in, for example, geography, economics and astronomy, due to seasonal effects. This is the case here too, for demand vs temperature (Figure 2.1). Both series have a pronounced
annual cycle which is dominating the outcome of the correlation.

We may ascertain, clearly, that in this case demand is being forced by temperature, and therefore that $r$ is physically reasonable. It must be remembered that this is mostly due to seasonality. It does not necessarily imply that short term (between days) fluctuations are correlated. Section 2.4 introduces the way we will show this.

2.3.3. PROBABILITY DISTRIBUTIONS AND NORMALITY

Classical linear regression theory requires that each series is normally distributed (or very nearly so). The significance tests described also require this criterion to be met. If it isn't satisfied, then statistical inferences from the results are invalid. An additional prerequisite is that the residual errors be normally distributed, with a mean close to zero.

The assumption of normality was tested by (for the purposes of this normality test only) normalising all raw data, i.e. raw becomes $(\text{raw} - \text{mean})/\sigma$. If a series is not skewed then the standard deviation of these normalised values should be equal to unity. Their mean should always be equal to zero irrespective of normality. All series were so tested. Most were found to be normal; those that were not will be discussed as they arise. There are other tests of normality, such as plotting cumulative frequency against class limits on special probability paper. If this approximates to a straight line, then normality can safely be assumed.

As an additional visual confirmation of normality, we will be using the frequency distribution. Here, the relative percentage frequency (which can be thought of as a kind of probability) is plotted against a scale in normalised deviations from the mean (i.e. standard deviations from the mean). A simple example, for the raw Gatwick temperatures, is given in Figure 2.2a. The data is approximately symmetrically disposed about the mean, indicating no radical departures from normality.

Figure 2.2a is actually a discrete probability density
Figure 2.2: a) The probability distribution of the raw Gatwick temperatures; % frequencies are for x-axis bands (classes) of sigma/4 units.

b) The spectrum ("periodogram") of raw electricity, for the first 60 wavenumbers.
function. The area under it can be visualised as proportional to the probability of an observation falling in that range. As the sample size approaches infinity, and as the intervals on the abscissa become infinitely narrow, we can see that our discrete distribution should approach the continuous Gaussian curve, if normal.

The frequency distribution in Figure 2.2a can thus be referred to as an (empirical) probability distribution. It is a property of any near normal distribution that 68% and 95% of values lie within 1 and within 2 standard deviations of the mean, respectively. This will prove to be a very useful result. There are additional statistics that describe the shape of the distribution. These include skewness (the degree of asymmetry) and kurtosis (peakedness of the distribution), but we need not review these here.

2.4. SEASONALITY AND HARMONIC ANALYSIS

It was hypothesised at the end of Section 2.3.2. that most of the dependence of demand on temperature is due to the pronounced annual cycle in both (which, from now on, we will term "seasonality"). If this is true, then uncovering this (seasonal) temperature dependence serves only to reveal in an overall or aggregate way how we respond to temperature on average through the year. It may tell us nothing at all about short term response. The low frequency variability is dominating or swamping the high frequency, inter-daily variability. Hence the next desirable step to test this hypothesis would seem to be to remove this systematic and predictable annual wave. This will then allow investigation of the nature of short term sensitivity, which confirms the need for its elimination.

2.4.1. BACKGROUND THEORY OF SPECTRAL ANALYSIS

Suppose, then, we suspect that a series contains a deterministic sinusoidal component at a certain frequency. In this case its period is precisely one year. The simplest way of identifying and removing such an annual cycle is to fit a least-squares sine curve, to represent an approximation to the annual cycle.
Commencing with the equation:

\[ Y = A \sin(\theta) + B \cos(\theta) \]  \hspace{1cm} (2.11)

we need to calculate the amplitudes A and B. Because of the orthogonal properties of sines and cosines, these are computed independently. An exact analytical solution can be arrived at by first recognising that the sum of squared deviations (SSD) from the sine wave must be minimised, where:

\[ \text{SSD} = \sum (Y - A \sin(\theta) - B \cos(\theta))^2 \]  \hspace{1cm} (2.12)

Taking the partial differentials of this expression: \( d(\text{SSD})/dA \) and \( d(\text{SSD})/dB \), setting them equal to 0 and checking their second differentials are >0 (for minimum), then after some algebraic manipulation and solving 2 simultaneous equations, we obtain the optimal numerical solutions for A and B. The phase angle (\( \phi \)) can then be obtained from the equation:

\[ A \sin(\theta) + B \cos(\theta) = C \sin(\theta+\phi) \]  \hspace{1cm} (2.13)

where: \( C = \sqrt{A^2 + B^2} \) and \( \phi = \tan^{-1} B/A \).

This procedure is equivalent to using Fourier (harmonic) analysis to calculate the Fourier coefficients (A and B) in the equations:

\[ A_j = \sum \{\text{RAW}(i) \times \cos(2 \pi j/N) (i-1)\} \times \frac{2}{N} \]  \hspace{1cm} (2.14)

\[ B_j = \sum \{\text{RAW}(i) \times \sin(2 \pi j/N) (i-1)\} \times \frac{2}{N} \]

where I is point in series (1..365), j is wavenumber (=1 here)

This is not a Fast Fourier Transform, see Brigham (1974) for details of that computationally faster version.

The sine waves fitted to Figure 2.1 are, then, their
wavenumber 1, using:

\[ \text{SEAS}(k) = A_0 + A \sin\left(\frac{\pi k}{180}\right) + B \cos\left(\frac{\pi k}{180}\right) \] ----(2.15)

where \( A_0 \) is time mean, \( k \) is point in series, and \( \text{SEAS} \) is seasonal component (sine wave)

By analogy with the minimisation approach, this expression is equivalent to:

\[ \text{SEAS}(k) = A_0 + C \sin\left((\frac{\pi k}{180}) + \phi\right) \] ----(2.16)

The whole series can be reconstructed by summing over all constituent wavenumbers. For demand and temperature, 79% and 72% of the variance is explained by their wave one.

2.4.2. THE PERIODOGRAM OR WAVENUMBER SPECTRUM

A very convenient and useful visual display of a record's spectral properties is the "periodogram" or "spectrum". Such is Figure 2.2b, which presents the spectrum of the raw daily electricity data. The abscissa is a scale increasing in wavenumber (\( j \)) but decreasing in period. The wavenumber is also related to the frequency, therefore, since it measures the number of complete cycles the \( j \)'th wavenumber executes during the period of wave \( j \). This period is called the "fundamental period", which is exactly one year here.

Figure 2.2b shows how dominating the annual cycle is in terms of its amplitude (point A). It also shows a further feature of interest. None of the other wavenumbers dominate, except wave 52 (point B). This results from the weekly cycle being picked up, which explains an additional 6% of the variance.

This kind of diagram will be useful later as it shows the relative contribution of each harmonic to the total variance. Instead of plotting amplitude as ordinate, some authors prefer to plot the power of each wavenumber (where power = \((C**2)/2\)). The periodogram then becomes a "power spectrum". This too is a measure of the variance explained.
by each harmonic, but since we will always be quoting this anyway (as $r^2$), the convention in Figure 2.2b of plotting amplitude versus wavenumber will be adhered to throughout this study.

"Fourier" or "spectral" analysis, when performed in this way, can be useful for describing time series which vary sinusoidally (and periodically). It has found wide success in areas such as oceanography, geophysics and marine science where periodic cycles are common (e.g. seasons), and in the physical sciences as a whole. There are, unfortunately, a number of important drawbacks to the approach.

2.4.3. SOME PROBLEMS OF FOURIER DECOMPOSITION

A difficulty sometimes encountered with spectral decomposition is that higher harmonics at integer multiples of the basic frequency can be accidentally generated, which cannot be interpreted as being associated with independent cyclic components in the data.

The generation of such harmonics was demonstrated by running the above spectral analysis on a square wave. This regular square wave with a period of 10 time units is shown in Figure 2.3. When put through a spectral analysis, harmonics are generated at waves 30 and 50 (Figure 2.3).

At first thought, a harmonic fit would seem physically sensible, since the astronomical forcing of demand by the annual temperature cycle is sinusoidal. What's more, one would perhaps anticipate that the seasonal normal (average for time of year) demand is forced by seasonal normal temperature. Fitting sine waves is really equivalent to taking long term means for each day of the year. We shall see now that this is invalid. Incidentally, too, the annual temperature wave (seasonal normal temperature) is not quite perfectly sinusoidal (faster heating in Spring than Autumn cooling). Also, on a global scale, it lags behind astronomical forcing by 1 to 2 months, due to the massive thermal capacity of the oceans.

The real problem with this approach is that long
Figure 2.3: A regular square-wave function (period 10 units) and its harmonic spectrum.
sections of the data are consistently over- or under-estimated by the harmonic fit (Figure 2.1). This means that the method fails to fit short term (inter daily) variations. In effect, cross correlating the resulting deviations of demand and temperature does not necessarily uncover short term sensitivity, but merely provides a measure of the efficiency of our sine fit method.

Harmonic analysis has been used here as an elucidation of seasonality and can be used for certain coarse time scale applications. For daily data later on, an alternative strategy will be devised, based on stepwise interpolation of seasonals. For the present application, the wavenumber one representation will be used to separate out and eliminate seasonality.

The general process of taking away seasonality will be referred to as "deseasonalisation" or "seasonal adjustment". There are alternative methods of carrying it out. For example, differencing or smoothing could be used; these will be discussed in Section 2.6. The U.S. Census Bureau "X11" program, widely used in the Department of Energy and various other energy authorities, uses moving averages and iteration to adjust for seasonality (see Shiskin (1967)).

The weekly cycle must also be removed, a process that will here be termed "deweeking" for "removal of the weekly cycles". The resulting data will be referred to as "deweeked data". Details of the method will be given later.

The deviations of deweeked demand and raw temperature from the annual cycle (wave 1) will be termed "residuals" or "deviations". When such demand and temperature residuals were cross correlated, \( r \) was found to be \(-0.61\). With a \( t \)-value of 14.7, this is still highly significant (despite being lower than the raw correlation). We thought most of the dependence was in the annual cycle; maybe it still is and our representation of seasonality is inadequate. The method does clearly overlook short term variations, being a smooth fit, as already mentioned. Can we infer from the residual cross correlation that there is any short term sensitivity at all? The cross correlation is surprisingly high. Why should this be so?
2.5. PERSISTENCE AND PERIODICITY

2.5.1. PHYSICAL MEANING AND STATIONARITY

We have been thinking of seasonality as a quasi-deterministic, systematic constituent. Demands are higher in winter, lower in summer. Therefore, on average throughout the year, days with high demand tend to follow days with high demand, and vice versa. There is said to be a high degree of "persistence" or "temporal coherence" in the data. "Autocorrelation" and "serial correlation" mean exactly the same thing, and will be used interchangeably as such. This concept of persistence and all its implications is of fundamental importance. It can perhaps be visualised intuitively as a kind of inertia or momentum in the system.

It should be emphasised here that this turns out to have far-reaching implications for our multiple time series applications. It is an area which is all too often neglected, despite implicit recognition of its fundamental importance. It is notoriously difficult to treat, but is a central notion to any application of cross correlation techniques to time series analysis. The whole issue is an idea we will return to repeatedly.

Only very seldom in nature, and in meteorology too, are observations independent of the remainder (i.e. not influenced by the order in which they occur). In marine science, geophysics and geography, for instance, time series frequently occur with a high degree of temporal coherence. In meteorology, temperature and windspeed, for example, are usually dependent on previous conditions, though this dependence diminishes with the length of time interval between events. This quality of persistence or coherence is very significant in meteorological statistics. It is the tendency of events not to occur in isolation but to stick together; high or low values tending to occur in groups.

It seems sensible to ask the question of how well future temperature or demand can be predicted as a function of past values. For temperature, this so-called "persistence method" turns out to be quite a good forecasting method. For demand, this constitutes an important and sophisticated
branch of time series modelling. Past demands can be of such forecasting value for future demand in the "autoregressive" and "exponential smoothing" suite of models, discussed later.

It has been noted that the raw demand-temperature correlation is high because of seasonality. This, then, is in effect the same thing as persistence, or, more precisely, is a manifestation of it. This persistence implies that the number of independent values \((n)\) within each series is considerably less than the sample size \((N)\). Independent values are those not influenced by any preceding values. This idea is rather difficult to quantify but it does, as a consequence, become necessary to estimate \("n"\) in order to evaluate the results correctly. It would otherwise be difficult to judge the validity of \(r\), since standard significance tests assume total independence within each series. The very existence of autocorrelation effects confirms that this assumption is not valid. It is this value of \(n\), not \(N\) as normally practised, that should be used when consulting significance tables.

Unfortunately, due mostly to historical reasons, the degree of temporal independence is not ordinarily tested. It is commonly assumed, as a legacy, that all the values within each series are independent, i.e. as though selected at random. This is very much not the case here.

It is desirable to remove (or take into account its existence in significance testing) as much persistence as possible. This is philosophically quite distinct from the problem of trying to understand why persistence exists in the first place. Regarding the former, we have already, in essence, identified the need to remove the annual cycle because of the serial correlation and its effect on \(r\).

We now know, then, that the original high \(r\) value was induced by persistence, and that there must be few independent values in the raw data. Now the annual cycle has been taken away, we are getting closer (one would hope) to the real short term sensitivity (assuming seasonality was specified correctly).
Ideally, one would hope to remove all systematic effects (trend, seasonals, cycles) so as to make the series "stationary". A stationary series is one possessing no systematic change in the local mean (i.e. trend) or variance (homoscedasticity) and no strictly periodic variations. Any remaining cross correlations will be true ones (not induced by persistence). Long stationary series occur, for example, in geology (e.g. seismology), statistical quality control, and queueing theory, but very rarely in meteorology.

2.5.2 STOCHASTIC PROCESSES

Most of the theory of time series analysis is concerned with stationary series. We are often required, therefore, to reduce the series to stationarity so as to use this body of theory wisely. Hence one would normally be interested in removing all predictable components and then modelling the residuals. This is sometimes referred to in the literature as "prewhitening", especially in engineering. It means to make the series random or "white noise" (white because its spectrum is similar to white light, and noise because there is no pattern). Such a record is also termed "stochastic" (as opposed to deterministic) meaning governed by the laws of chance or probability. Most natural processes in reality involve a random or stochastic element in their evolution. Chatfield (1975) quotes the familiar examples of the length of a queue or the size of a bacterial colony, but erroneously quotes daily temperature as an example. Queueing theory is, then, another field making use of random processes, e.g. flows in telecommunication theory. See Grenander and Rosenblatt (1957) for the theory of stationary series.

The stochastic modelling of residuals is an advanced branch of theoretical time series analysis involving, for example, moving average or autoregressive models of them, and differencing (see Section 2.6.2). This is the basis of the Box-Jenkins approach, described later. A variety of complex probability models, collectively known as "stochastic processes", can be fitted to stationary series.

* Hereafter, "stationarity" will refer to a random series, with no short-term persistence.
Chatfield (1975) defines a "stochastic process" as a statistical process that evolves in time according to probabilistic laws.

The cross correlation techniques adopted here, though perhaps (debatably) not as rigorous as these, have firm physical foundations. This will form an important prerequisite of later work.

2.5.3. TESTS OF RANDOMNESS

The extent of autocorrelation (degree of persistence) is quite clearly a very important thing to quantify before any attempt is made at modelling. This provided the greatest motivation for using the following tests. We now describe four tests of randomness; the first is believed to be novel, and was derived specifically for the applications in this study. It is the only one that produces an estimate of \( n \), and is probably the most powerful of them. The remainder are semi-standard, but modified for application here. Such tests are here thought to be applicable in many areas such as engineering, operational research, statistical quality control (industrial applications), seismology, astronomy, and are useful where controlled experiments are carried out, in industry and research. They are ubiquitously used in certain of them already, but not in others.

These tests will normally be performed on residual series, as raw series are clearly not random. They will not all be performed on every residual series, sometimes only one test, sometimes more than one in borderline cases to supplement each other, or to amplify certain points, depending on the application. Here, they will be described and exemplified with real data.

There are many others and the literature is full of interesting variations; see, for example, Kendall (1973), Brooks and Carruthers (1953). They can equally be regarded as tests of persistence, as they provide a quantitative and objective measure of it. Some are simultaneously tests of periodicity. All of them were tested on random series, square waves, saw-tooth functions and perfect sine waves, etc. The results of this experimental background are not
shown, here, suffice it to say that they accorded with expectations and demonstrated the power of the tests.

2.5.3.1 THE CORRELOGRAM

The first test was designed to produce a numerical measure of the degree of temporal coherence. It is also particularly useful tool for investigating any suspected periodicity, its strength and frequency. Additionally, it supplies a quantitative estimate of the number of independent values (n).

It will be the most commonly used test in this work. It concerns the idea of autocorrelation, which has already been mentioned in a descriptive and intuitive sense in relation to persistence. It can be defined precisely here. Autocorrelation means correlation with itself. Autocorrelation coefficients are ordinary ones like those already encountered, but between a time series and itself, at different intervals apart. These intervals in time are termed "lags". For our purposes, the autocorrelation coefficient at lag k, \( r(k) \), will be informally referred to as "lag r". This statistic is one way of representing numerically the degree of persistence or serial correlation.

A very helpful tool in interpreting a series of \( r(k) \)'s is the "correlogram", in which \( r(k) \) is plotted against the lag k. This is termed the "autocorrelation function" (Acf). Interpretation is often difficult and subjective but a visual inspection and interpretation should always be attempted.

Clearly, at zero lag there is perfect autocorrelation (\( r(0)=1.0 \)). For a series with high persistence, the Acf falls off or dampens slowly. For random series, there is no persistence and hence all the \( r(k) \)'s are close to zero (i.e. the autocorrelation vanishes). For series containing periodic oscillations, the Acf also oscillates at the same frequency (and at integer multiples of it). Thus the Acf's behaviour can be useful in detecting periodicity and uncovering the underlying nature of variability in the series.

The residual electricity demand series and its
correlogram are presented in Figure 2.4. The convention adopted here is that for correlograms, crosses will be marked at each point on the plot, but in general on the time series themselves they will be omitted. The horizontal lines on the Acf will be explained shortly.

We would like to test these residuals for stationarity. On examination of the correlogram (Figure 2.4b), there is a high degree of persistence, as indicated by high lag correlations for short lags. The series is obviously nothing like stationary, even though seasonality has been taken away. We now need to determine the extent of serial correlation numerically in order to find n.

It can be shown (Chatfield 1975) that if a record is totally random, then the lag r's are normally distributed with zero mean and a standard deviation of 1/N. The usefulness of this arises because if random, then 95% of the lag r's should lie within +/-1.96√N. The full horizontal lines on Figure 2.4b are these 95% confidence limits for the Acf. This convention will be adopted for all correlograms. Clearly, more than 1 in 20 (>5%) of the lag r's fall outside this band, indicating non-randomness in the electricity residuals.

Furthermore, the degree of serial correlation can be estimated by noting at what lag the Acf falls to within these limits, i.e. at what lag the autocorrelation becomes insignificant. We shall term this lag the "Effective (or Equivalent) Number of Repetitions" (ENR), or, more intuitively, "lag time". The nearest integer lag above (numerically) this point will be chosen for ENR, to be on the safe side. This means the persistence is not underestimated. The ENR was coined by Chapman and Bartels (1940), who used it in a quite different (actually geophysical) context not involving the correlogram. Their technique was originally applied to studying periodicity in geophysical time series, such as magnetic disturbances or sunspots. The great interest in, for example, solar-weather relations (e.g. Hines and Halevy, 1977) has led to its potentially greater applicability in meteorology too. Their test involved computing ENR numerically (not graphically as
Figure 2.4:  
(a) The electricity demand residuals (i.e. deseasonalised and deweeked demand).  
(b) The residual correlogram (the horizontal lines are the 95% confidence limits for lag r, see text
here). Lewis and McIntosh (1952) show how ENR can be calculated from a series of serial correlation coefficients.

For the electricity residuals (Figure 2.4a), there is persistence out to a lag of about 15 days (Figure 2.4b), therefore ENR=16. The reason why any persistence remains after removal of the annual wave is the failure of the sine wave to fit short term variations. It overlooks these and in doing so induces persistence in the deviations. The method of sinusoidal annual cycles is therefore not very sound.

Finally, from ENR one can calculate \( n \) using:

\[
 n = \frac{N}{(ENR+1)} \tag{2.17}
\]

The +1 is necessary to ensure there are \( N \) independent values if persistence (ENR) is zero. For the electricity residuals, \( n \) is 21, i.e. there are only 21 independent values in 365 days. If we now go back and retest the significance of the residual correlation of \( r=0.61 \) (t=14.7), the significance would be lowered when using \( n \) and not \( N \), though not noticeably in this case. Such determination of \( n \) will always be performed on both series involved in the cross correlation, and that with the lowest \( n \) used for significance testing. In all future quotations of statistical significance, \( n \) will have been explicitly used (not \( N \)), though this important fact will not be repeated at each significance test.

It should be noted that one should not compute autocorrelation coefficients for lag times exceeding \( N/3 \). This is because the Acf behaves somewhat erratically at greater lags due to the ever decreasing sample size at lags \( >N/3 \) (at lag \( k \) there are \( N-k \) terms for the computation of \( r(k) \)). Hence all future correlograms will be strictly terminated at lag \( N/3 \). This is why the horizontal confidence limits do not diverge with increasing lag (as might be expected), since curtailment at \( N/3 \) takes care of sample size and hence significance.

It is also worth bearing in mind that even if a record is stationary, then paradoxically one can expect, just by chance, the occasional \( r(k) \) to lie outside \(+/-1.96\sqrt{N} \).
Accidental or spurious autocorrelations can occur in the same way as for ordinary cross correlations. Judgement is hence necessary in borderline cases and a different test may be required to supplement this one.

The interpretation of correlograms is sometimes not easy and considerable experience is often required. Here we have offered some specific advice in relation to our method of deriving ENR and n, which is believed to be original. Further more general advice can be found in Chatfield (1975).

2.5.3.2. SUPERPOSED EPOCH ANALYSIS

This method has two quite distinct areas of application: namely to investigate:

1) hidden periodicities or recurrence tendencies within a single time series (univariate superposed epoch analysis),
2) the relation between two corresponding series.

Attention here will be confined to the former, since we will have ample methods for the latter.

If a record is suspected to contain any kind of cyclical behaviour, the univariate version will uncover it if present. It is therefore explicitly a test of periodicity as well as an implicit test of randomness, as a result. It can reveal the frequency of periodic variations, but does not provide a measure of persistence.

In essence, if we suspect oscillations every \( t \) days, say, the method calculates the means of values \( t \) days apart to confirm (or otherwise) periodicity at this frequency. These means are computed separately, starting from 1 to \( t \) time units sequentially. The "key time" (i.e. the time around which we suspect periodicity, or the centre of the cycle) will therefore lie at \( t/2 \) time units from the start of the series. In other words, means are calculated on either side of the key time in the range \( +/- t/2 \). The variation of the procedure adopted here assumes that these key times are regularly spaced along the series.

Though one would normally apply such a test to a residual series, it will be briefly applied to the raw demand here. This is simply to provide a clear illustration of the method. Let us suppose, for simplicity, that cycles
are suspected every 7 days (i.e. the weekly wave). Hence the key time is Wednesday. Figure 2.5a shows graphically the distribution of the means (as described above) about this day, i.e. means for each day of the week in this case. The routine was written for general use on various time scales, hence the general term "time units" on the plot. The weekly cycle is clear from these means (Figure 2.5a). This was obvious anyway, but in an (apparently) random noise series it might be rather more subtle. The statistical significance may be established by examining departures of these means from the general mean of the complete record. This will be unnecessary here since all cases to be examined are sufficiently clear cut.

This technique has all sorts of interesting applications in, e.g. geophysics, and has the advantage over Fourier analysis that oscillations need not be sinusoidal.

2.5.3.3. TURNING POINTS

A somewhat simpler test, particularly when the record has been plotted, is to count the number of turning points (local maxima and minima). This is then compared with the expected number if random. This test is quite widely used in economics, oceanography and geography, amongst others.

If random (i.e. pure white noise), and since 3 consecutive values are needed for a turning point, then 3 values could arise in any of 6 possible arrangements with equal chance. Only 4 of these combinations would allow a turning point, namely those with the largest or smallest as the mid point. The chance of a turning point in a set of 3 values is therefore 2/3. For N values, the expected number of turning points (E) would be given by:

\[ E = (N-2) \times \frac{2}{3} \]  ---(2.18)

if random. One must use (N-2) because one cannot regard the end points as defining a turning point. Kendall (1973) quotes the appropriate significance test; again all our cases will be sufficiently clear cut and unambiguous to warrant avoiding this.
Figure 2.5:  

a) Superposed epoch analysis of raw electricity demand cycle suspected every 7 days (the annotation refers to days of the week).  
b) Spectral analysis of demand residuals.
2.5.3.4. SPECTRAL ANALYSIS OF RESIDUALS

The technique of constructing a spectrum of amplitude versus wavenumber, as we did in Figure 2.2b, is not usually applied to raw data. This is because the cycles are usually very obvious there. An approach that will be used throughout is to put the residuals through a harmonic analysis, since any remaining periodicities embedded in them will be very sensitive to Fourier decomposition.

Fourier analysis of a stochastic noise series would produce a spectrum exhibiting no preponderance of any particular wavenumber. As an illustration, Figure 2.5b (the spectrum of the electricity residuals) shows that the lower harmonics are dominating the spectrum, supplementing the evidence for serial correlation in the residuals.

2.6. TREND

So far in this treatment, we have considered cyclical behaviour (periodicity) in the form of the annual and weekly cycles, and also the residuals or irregulars. There is another important constituent of most time series. This is trend. Trend can be loosely defined as "long term change in the (local) mean". This is probably the most useful and practical definition for our purposes. Its precise meaning depends on the time scale. For many years of the daily data in Figure 2.1, it would be the interannual variability, i.e. the long term (over several years) changes.

There are many methods of dealing with it; we summarise here the most important of them. This Section is a resume of the methods investigated, and those abandoned in favour of a unique method to be presented later.

2.6.1. MOVING AVERAGES AND THE DANGERS OF SMOOTHING

2.6.1.1. RUNNING MEANS IN GENERAL

This area embraces a large variety of techniques and as such it constitutes an important area of statistical analysis. This Section is an overview of what is involved.
A common method of estimating trend is to use moving averages or running means as representations of it. These are used to "smooth" the series, so as to filter out high frequency variability. The simplest form of such a "low-pass filter" is the non-weighted moving average. The width of the running mean can be varied, and various combinations of weights can be used, usually attaching greatest importance to the central value. Several end-points are lost, depending on the width of the mean. Special procedures are available for dealing with end-points, but are omitted here. Either way, this filtering would generate a trace in which the spectral components at high frequencies are reduced. It is termed low-pass, since low frequency (long period) components, that is low wavenumbers, are little affected. Such a smoothed series is simply a guess of what the value would have been (i.e. trend) in the absence of high frequencies.

One can also filter out low frequency oscillations ("high-pass filters"), or filter out both low and high frequencies to leave only the medium frequencies ("band-pass filters"). A common type of filtering is "exponential smoothing" (which is actually that produced by most meteorological instruments).

2.6.1.2. SMOOTHING RANDOM NUMBERS: AN EXPERIMENT

By far the greatest disadvantage of smoothing lies in a hidden subtlety in its effect on the spectral composition of a record. To emphasise the importance and danger of this effect, we will consider a purely random trace (a hypothetical "white noise" sequence). This is shown on Figure 2.6, together with its correlogram and periodogram. This artificially generated random series (noise) consists
Figure 2.6: An artificially simulated random record and its autocorrelation function and spectrum.
of 50 values with, purely for convenience and arbitrarily so, a mean of zero and a standard deviation of unity. The complete absence of any persistence or periodicity in the Acf and the chaotic pattern in the spectrum, testifies to its randomness.

If a 3-point moving average is applied to the random trace, the resulting smoothed series is shown in Figure 2.7, again accompanied by its Acf and spectrum. The low pass filter has actually introduced some persistence into the data. This is evident from both the smoothed data itself and from its Acf. The Acf shows that serial correlation has been introduced out to a lag of 1 time unit, beyond which the Acf dampens rapidly. There also appears to be some weak cyclical behaviour in the Acf. In the harmonic spectrum too, the relative wave magnitudes are no longer haphazardly disposed. Certain wavenumbers have visibly been enhanced. In particular, waves 1, and 5 to 8, are now exaggerated. In general, low frequency variations have been emphasised at the expense of high frequencies.

If one was searching (or testing) for cyclical behaviour or persistence in a quasi-random residual series of real data, and if smoothing had been used at any stage (as it all too often is), then we might uncover fictitious persistence and periodicity such as this. This would be very misleading, especially with respect to physical meaning. One would not know whether this was real or not. Figures 2.6 and 2.7 are a useful experimental verification of an important effect. Simulating or artificially generating imaginary random series will also come in very useful later in another context.

An additional danger (actually a corollary) is that the amplitudes of individual waves are affected differently. Some cycles are damped more than others. This induced periodicity we have already noted from the Acf of the smoothed random record. They are merely a figment of the smoothing technique, and one should once again beware of the fallacy of attributing them to physical causes. This is thought here to be the method's greatest weakness.

The "frequency response" of a filter is an expression
Figure 2.7: Illustration of the dangers of smoothing: a 3-point moving average (low-pass filter) of the random white noise series in Figure 2.6, with its ACF and spectrum.
of how different waves are affected. For instance, our 3-point moving average generated oscillatory behaviour of period around 6 units. It has been found that attaching binomial weights in the moving average partially suppresses induced periodicity.

For more information on filtering in general, see Craddock (1968), and Bennett (1979) for related statistical areas.

2.6.1.3. OTHER DANGERS OF FILTERING

Another danger in the method, which we will mention only in passing, is that moving averages are very sensitive to extreme values. This too is an undesirable property. It is particularly important, too, to be wary of taking repeated running means of the same series.

An additional complication of the approach concerns reproducibility. We stated, as one of our prerequisites of model building that we must always be able to reproduce the raw data. A problem with filters is that they are non reversible.

A further restriction of the approach was in physical interpretation. Earlier we stated that a fundamentally important part of the philosophical foundation of decomposition is the attachment of physical meaning to each component. A trend defined by a running mean has no physical meaning whatsoever.

2.6.2. POLYNOMIALS, EIGENVECTORS AND DIFFERENCING

Other methods are available for trend fitting, but also suffer from interpretation problems. For example, fitting least squares polynomial curves as a representation of trend was abandoned. This was because serial correlation was introduced into the deviations from it (residuals), unless the curve fit is of a very high order. This problem was also present in the harmonic fit approach. Unlike sine waves, polynomials have no physical meaning. One
can, if desired, split the record into segments and fit polynomials to each one independently. A class of such piecewise polynomial fits are known as "spline functions", see, for example, Wold (1974).

Likewise, eigenvectors (empirical orthogonal functions), because of their mathematical basis, rendered any extraction of physical meaning difficult. It is not clear which components are absorbed into which eigenvector (annual, weeks, etc). Furthermore, taking the first eigenvector as describing the annual cycle (if this is justified), to interpret deviations from it, and the autocorrelation therein, are also difficult and very subjective. See Tress (1979), B.Sc. Thesis, for a principal components analysis of 10 morphometric variables, in a hydro- meteorological application of eigenvector analysis. See also Essenwanger (1976) for a general treatment, and McGuigg et al (1972), Matthewman and Nicholson (1968) for energy meteorology applications.

Differencing is a technique that will be described and exemplified later. Here too there are some problems of interpretation, but remarkably the persistence issue becomes completely resolved in it, as we shall see.

Trends should never be used for forecasts. Trend forecasts (projections) use only the series from which the trends were derived (i.e. univariate) and therefore use no weather information. As we shall discover in the case studies, we will have perfectly adequate ways of representing trend, and will use cross correlation techniques to bring in the use of meteorological data. The method to be derived there is novel and copes with both local and long term trend.

2.7. BOX–JENKINS MODELS: A SHORT NOTE

There is at present a growing body of opinion among statistical circles that Box–Jenkins forecasting models are the best. This is spreading into the fuel industries too, where it is becoming fashionable to adopt them for energy meteorology applications. Their volume (Box and Jenkins, 1970) is a very famous contribution to time series analysis.
The present generation of such models is likely to be implemented within the fuel industries within the next 5 to 10 years. Some Area Boards are already in the process of converting to them, though most still use linear or even manual methods. Despite their sophistication, they have no physical basis. They are rather time consuming, and demand a considerable amount of skill and programming expertise. The details are therefore beyond the scope of this primarily meteorological study. The Univariate variety uses only past demand data (no weather information), and bivariate versions use only temperature.

Nevertheless, they will prove to be of some relevance later in various contexts. The author has had some experience of Box-Jenkins models at the Department of Energy (London), and since we will meet them again, it might be useful to briefly summarise their background.

Basically, the method reduces the demand series to stationarity (stochastic white noise) by suitable differencing operations. We then derive the best stochastic model for the demand residuals (still univariate at this stage), i.e. establish the operator that best converts a random series into our residuals, this is the so-called model identification stage. Schematically,

Univariate Box-Jenkins model

```
RANDOM SERIES ------- OPERATOR OR FILTER ------- DEMAND RESIDUALS
```

Effectively, we are asking “which operator (e.g. smoothing process), when acting on a random trace, produces our record? This is a very interesting consequence (actually the reverse) of the phenomenon of smoothing random numbers already debated. Alternatively, “which autoregressive scheme, applied to a random series, produced our stochastic residuals?” These are known as “Moving Average” (MA) and “Autoregressive” (AR) models respectively, and constitute an important class of stochastic models. Mixtures are possible between these suites of models, e.g. we could fit an
"Autoregressive Integrated Moving Average" (ARIMA) model, and the Box-Jenkins method involves advanced stochastic theory as a result. These are far too complicated to permit the extraction of physical meaning. Exponential smoothing (a branch of the autoregressive family) predicts demand as a function of weighted previous values. An intuitively attractive sequence of weights would be geometrically decreasing ones; this method will be used in a later case study to smooth daily temperatures.

Both temperature and demand residuals are put through the best stochastic model for the demand residuals ("prewhitening"). A "transfer function filter" is then devised iteratively that transforms the input series (temperature residuals) into a series which, when added to some noise record, reproduces the output series (demand residuals). In conceptual form, the idea can be represented as:

```
Bivariate Box-Jenkins model

RANDOM • NOISE • NOISE SERIES
--------- ------ -------------------
INPUT SERIES
(TEMP RESIDUALS)
--PREWHITENED--
TRANSFER FUNCTION FILTER
--OUTPUT SERIES
DEMAND RESIDUALS
```

Multivariate versions are also available. Chapter 1 detailed the energy meteorology applications of the method as a whole. The above exposition is necessarily only scratching the surface, but will be of relevance later.

2.8. MULTIVARIATE CROSS CORRELATION TECHNIQUES

2.8.1. THEORY OF STEPWISE MULTIPLE REGRESSION

It is often useful in statistical weather-demand analysis to investigate the effects of several meteorological parameters simultaneously. Stepwise multiple regression analysis allows this by first regressing one variable, say temperature, on demand, and then step by step...
adding further variables (say windspeed or sunshine), normally in their order of importance. The multivariate regression model then becomes:

\[ Y = a + b \cdot X_1 + c \cdot X_2 + d \cdot X_3 + \ldots \]  

---(2.19)

where: \( X_1, X_2, X_3 \) are independent variables, \( a, b, c, d \) are multiple regression coefficients.

The aim is to extract an optimal number of variables which together explain some pre-defined "satisfactory" amount of the variance in \( Y \). The usefulness of adding each variable can be realised by examining the increase in \( R^2 \) (variance explained) at each step. Adding a variable, say \( X_2 \), can be conveniently thought of as regressing \( X_1 \) on \( Y \), after \( X_1 \) has been corrected for the effect of \( X_2 \). This is, after all, how the routine computes the statistics, and is exactly similar for further variables. The increase in \( R^2 \), therefore, reflects the additional explanatory power of \( X_2 \), after that of \( X_1 \).

The fundamental principles of multiple cross correlation are analogous to those of the univariate case. They can be found in standard statistics texts (e.g. Spiegel (1972)) and will not be repeated here, except for a few general comments. Essentially, they are all generalisations of the 1 variable case. See also Journal of Multivariate Analysis for a variety of different applications.

For example, the multiple cross correlation coefficient, still denoted by \( r \), and \( R^2 \) (now the coefficient of multiple determination), SEE, etc, are directly analogous to the linear case and have similar meaning. Instead of minimising the total squared deviations from a straight line, we are now minimising those deviations from a regression plane in 3-dimensional space (for 2 independent variables) or from a hyperplane in 4-D space (3 variable case). The multiple regression equation, then, represents a surface in a 3-D rectangular co-ordinate system (2 variable case). For even more variables, it is obviously impossible to visualise, being a mathematical abstraction,
but it is perfectly legal mathematically to minimise errors in multi-dimensional space.

In the multivariate situation, the b's become "partial regression coefficients", i.e. those obtained by keeping the remaining variables constant. This is necessary because, for example, Y varies partly due to variations in X1 and partly to variations in X2. "Partial" correlations, then, are those between 2 variables when the effects of all others have been removed. The equations quickly become rather tedious and are not reproduced here, see, e.g. Spiegel (1972).

The independent variables need not all be synchronous; they can be past values of Y, lagged to varying degrees (i.e. multiple lag cross correlations). If past values of demand are used, then these terms are "autoregressive" terms. As previously indicated, this was unsuitable for our applications from a meteorological standpoint.

In meteorology, several variables will be acting simultaneously on demand, and it is often physically justified to combine them, as long as we understand how they interact. The approach has proved very useful here, and considerable care was exercised in avoiding the inherent dangers in the method. These will now briefly be considered.

2.8.2. THE PROBLEM OF MULTICOLLINEARITY

2.8.2.1. GENERAL CONSIDERATIONS

Quite frequently in nature, and in meteorology too, the supposedly independent parameters are not quite independent. That is they may be inter-cross-correlated. This is known as multicollinearity and is recognised in the literature as problematical. For instance, if we were (as indeed we will be) correlating temperature and windspeed with demand, then because temperature and windspeed are (usually) correlated, it is not obvious how their interaction will affect their individual influence on demand. They are said to possess multicollinearity. It occurs when two or more parameters are serving almost the same purpose. It is most likely, as a result, to afflict models with many parameters. When it is pronounced,
estimates of model parameters (a, b, c, d in equation 2.19) become more sensitive to particular parts of the data base. Also, the inclusion of a few data points can produce substantial drifts in some parameters. As a result, it becomes difficult to disentangle the relative effects of the so-called independent variables, the number of which should therefore be kept to a minimum.

It is unnecessary for all parameters to be totally independent, indeed this is not very common. When multicollinearity is not serious or acute, these factors assume less importance. In future analyses, a partial correlation matrix of all the parameters will always be presented and examined.

If many variables are present, the problem of multicollinearity can be partially overcome by condensing the parameters into "principal components" or "factor analysis". See Johnson et al (1972) for example. Alternatively, "ridge regression" techniques provide more satisfactory models, e.g. Hoerl and Kennard (1970), which are finding application in cases of acute multicollinearity.

Another difficulty which sometimes arises in multivariate analyses concerns the structure of the error terms. Chatfield (1975) quotes that it is normally assumed that these are random. Having fitted a multiple regression model we will always check the residual errors for autocorrelation and normality, though the results will not always be presented. In addition, it is usually advisable to fit the model to part of the data base, and then test it by forecasting the remainder. This recommendation too will be followed.

2.8.2.2. AN OPERATIONAL RESEARCH/OPTIMISATION PROBLEM

A further problem, which merits a separate Section, and again one which will be avoided, is the temptation to put many explanatory parameters into the model. Economists and social scientists have a tendency to do this. The resulting model often appears to give very high explanatory power. This may be spurious and does not necessarily mean the formulation will produce good forecasts.
The model should still use as much relevant meteorological data as necessary. The construction of the model should really represent a compromise between using the least data consistent with the greatest predictibility. The simplest model, and from that point of view the most desirable for manual bench demand prediction, is one with few parameters. Clark (1979), amongst others, maintains "the fewer variables the better". For computerised prediction, on the other hand, there are no practical constraints on the number of variables.

After adding how many variables do we fail to increase explanatory power? This can be ascertained by examining the increase in % variance explained ($r^2$) at each step. This illustrates the "law of diminishing returns" in cost-benefit analysis, and is actually an optimisation/ linear programming problem in Operational Research. The "objective function", in the jargon of operational research, is to maximise $r^2$, subject to constraints of number of variables and the presence of multicollinearity. In later case studies, several meteorological parameters will be involved and justified with respect to these considerations.

It turns out that none of the above problems will impede us, though we must always be careful to recognise their possible effects and indirect consequences which are often rather subtle.

Having covered the relevent statistical background and theory of multiple time series analysis, we are now in a position to apply this knowledge in practice, and proceed to the first case study.
CHAPTER 3

MODELLING MONTHLY COAL AND OIL CONSUMPTION:
A NATIONAL CASE STUDY

3.1. INTRODUCTION TO THE PROBLEM

Which time and space scale does one start with when investigating the effect of weather on energy usage? It seems reasonable, to gain an initial insight into the nature of consumer response in general, to select a fairly coarse scale. It is particularly useful and instructive to begin with a national case study of monthly coal and oil demand. This will help to iron out certain statistical and philosophical problems at this still quite early stage. It will also serve to clear up some standard analytical problems facing energy demand modellers, and can conveniently provide further illustrations of the statistical techniques.

It should be pointed out here that the nature and scale of this monthly data has limited the usefulness of meteorological information in this case study. As we proceed in subsequent Chapters to finer time and space scales, and to gradually more sophisticated techniques, this problem becomes increasingly less apparent. This coarse scale groundwork is necessary for the reasons outlined in Chapter 1 (spatial/temporal hierarchies, etc). It forms part of the necessary lead-up or preparation for more advanced considerations.

There are some restrictions on physical interpretation in data of this scale, since the data are contaminated by a variety of non-meteorological influences. In addition, short term responses are implicitly lost or smoothed out by this selection of scale. The results of the immediate case study should therefore be taken only as a general indication of consumer sensitivity to the weather. The study is interesting and useful in its own right, however, and does succeed in indicating the general scale and nature of this sensitivity.
3.2. THE OBJECTIVE

The most obvious atmospheric factor affecting demand is temperature. On this national, monthly scale it is probably the only detectable one too, others (e.g. windspeed, sunshine) being swamped or dominated by it. The incentive to model monthly coal and oil usage using temperature came partly from the above reasoning, and was also inspired by the Department of Energy (Economics and Statistics Division). This arose from their interest in "temperature correction". One can, having modelled this relation, temperature correct or adjust raw demand (i.e. remove the influence of temperature on it). This would yield a hypothetical demand series that would have occurred had temperatures been "normal". One could then investigate the effects of other non-meteorological variables. These might, for example, include the impact of Government energy conservation policies, trends in sales, fuel price variations, or a host of other economic/political factors. This case study, then, puts forward an example of the "weather normalisation" family of energy models discussed in Chapter 1.

The Department of Energy (DoE), amongst many other energy authorities, has for the purpose of weather "deweighting" or "normalisation" over the last 15 years, made several attempts at temperature correction. These range from fairly straightforward linear schemes to the more complex Box-Jenkins suite of routines. Until the advent of the latter, the DoE has shown some concern as to the validity of temperature correction models derived some years ago. They feel (personal communication) that a recent re-examination of present consumer sensitivity would be beneficial.

The more immediate objective of this case study, then, is to derive and critically assess a linear model of the monthly temperature dependence of national coal and oil (petroleum) consumption. This will allow the establishment of temperature correction factors (TCF's), which may then be used to normalise the demand series to one containing no temperature dependence. The TCF is here defined as the
percentage correction made to each point in the energy demand record for each 1 deg C temperature deviation from some pre specified "normal" value.

It is important to note that only in this particular case study will we be interested in temperature correcting, for the above reasons. Normally, we will be investigating weather effects and so would leave in the temperature dependence, rather than remove it. The actual modelling of the dependence (i.e. before temperature correcting) still has common ground with future Chapters. Having modelled the temperature dependence, so as to understand the effect of weather, we will normally want to go on to demand forecasting applications. Clearly, on a monthly time scale, this is not possible.

3.3. SECTORAL BREAKDOWN OF COAL AND OIL ENERGY MARKET

Before moving on to a description of the data base, it is important and interesting to be aware of the variety of end-uses of coal and oil, and the extent to which these uses are weather dependent. One has to be very cautious when working with energy statistics; and definitions, end-uses, etc., should be stated clearly. This Section provides a short summary of the customer class breakdown of petroleum and coal demand. It is necessarily brief, and should be read in conjunction with the pie-charts and reference statistics given in Appendix 1.

Petroleum accounts for 37% of all heat supplied to industry, coal 22%. For the domestic sector these figures are 8% and 23% (Appendix 1). Since these values were calculated on a "heat supplied basis" (see DUKES, 1982), one would expect an overall temperature dependence and a marked seasonal variation over the UK as a whole, on a monthly time scale. Since coal (and oil, to a lesser extent) is also used for electricity generation in conventional thermal power stations, we would also expect the temperature dependence of electricity demand to show through in the coal figures, on this time scale.

There are also very significant non weather-sensitive uses, such as transport (for oil), industry and part of the
commercial sector. To illustrate their importance, industry takes 31% of all petroleum sales, transport taking 51% and domestic only 5%. The largest industrial users of fuel oil are the steel, chemical and paper making industries. Similarly, industry takes 53% of all coal and solid fuels, and the domestic sector 40%. Iron and steel and power stations are the most important industrial customers. Of electricity generated at power stations, coal- and oil-fired plant accounts for 70% and 16% respectively (1977 figures). The remainder is nuclear, hep and gas turbine plant. Also in 1977, 65% of internal coal consumption went to power stations, 13% to coke ovens (for steel industry), and 9% for domestic (house coal).

At one time, the domestic sector would have been more important (coal fires) and therefore more weather sensitive. In modern times domestic heating is dominated by gas and electricity. Coal now has only a 10% share of the central heating market, and oil just 3%. Nevertheless, we will attempt to uncover any weather effects that may be present. See DoE (1979) for further clarification.

3.4. THE DATA BASE AND INITIAL ADJUSTMENTS

This Chapter, then, presents a summary of the results of a national case study of coal and oil consumption. The temperature dependence, and therefore the temperature correction model, will here be derived for two streams of energy data:

a) Monthly coal consumption for the 12 year period 1964-1975 (thousand tons). These were supplied by DoE in the form of Gross Inland Coal Consumption figures, for the UK. These data represent deliveries and as such include disposals by the National Coal Board to industry (including power stations for electricity, blast furnaces, iron foundries, etc) and to merchants for the domestic market.

b) Monthly oil (petroleum) consumption for the 13 year period 1967-1979 (Total Inland Oil Deliveries, 1000 tonnes). These include deliveries for electricity generation in oil-fired power stations. In addition to fuel oil, these figures also incorporate a large variety of petroleum
products such as motor spirit, derv for road vehicles and kerosene, amongst others.

Because both are deliveries (i.e. sales), and not actual demand, errors spring to mind immediately due to storage of fuels. Hereafter, for the purposes of this study, the words "demand" and "consumption" are assumed synonymous and are used interchangeably. The problem of deliveries, however, and all it implies about fuel storage and lags, should be recognised when attaching physical significance to the results. Similarly, "oil" and "petroleum" are freely interchanged.

The corresponding temperature data base consists of synchronous monthly average national temperatures. They are areal averages of 15 meteorological stations: 12 in England, 2 in Scotland, 1 in Wales; 5 are given a double weight in large conurbations, in an attempt to be representative of the spatial variation of consumption.

The nature of these data presented several initial problems which were overcome by various, statistically "legal" adjustments. These raw data are shown in Figure 3.1, together with the raw temperature series for coal (the temperature series for oil is very similar). Firstly for demand (Figure 3.1a, for coal), clear annual cycles are in evidence (seasonality), superimposed on which is the overall general trend (decline) and short term (inter monthly) fluctuations. For temperature (Figure 3.1b), seasonality is also present, but we can safely assume there is no trend in temperature over this period (i.e. negligible short term climatic change).

Closer inspection of coal demand (Figure 3.1a) also reveals a distinct and consistent 3-monthly peak in consumption levels. This apparent cycle arises because of a 4-4-5 week cycle in the monthly totals. Every 3 months there is a 5-week month; the intervening 2 months consisting of 4 weeks. These are so called "statistical months" as opposed to "calendar months". This is unavoidable since commercial coal and oil deliveries are recorded weekly. Every third month, therefore, was divided by 5/4 to normalise the series to one containing consistent 4-week months. The adjusted
**Figure 3.1:**

1. The raw (unadjusted) coal demand series, 1964-75.
2. The corresponding monthly temperature series.
Figure 3.1:  
c) The adjusted coal demand series 1964-75.  

series (for coal and oil), together with a strike adjustment to be explained presently, are reproduced in Figure 3.1c and d. These are the series we will be working with hereafter.

Regarding trend, the coal series (Figure 3.1c) exhibits a steady decline with time (long term trend) due to competition from other fuels, decreases in production and, more recently, the economic recession. The latter has meant a worldwide recession in steelmaking, which reduced the demand for coking coal towards the end of the period. The oil profile (Figure 3.1d) shows a marked decline since the 1973 peak, due to the international oil crisis, Arab-Israeli war, etc.

The trend in demand, and the annual cycles in both demand and temperature, are so pronounced and dominating as to necessitate their removal. This separation of the slowly varying, low frequency component will then allow investigation of the more noisy, high frequency variability (i.e. the irregulars). The following table illustrates the importance of trend, seasonality and irregulars (inter monthly), by summarising how much variance in the raw data they explain. For the time being, trend means variation of annual means, but this will be much expanded later.

Table 3.1: Relative apportionment of variance explained by all components, and the raw cross correlations between demand and temperature. By the additive properties of variances, all component variances sum to exactly 100%.

<table>
<thead>
<tr>
<th></th>
<th>Trend</th>
<th>Seasonality</th>
<th>Irregulars</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coal Demand</td>
<td>57%</td>
<td>39%</td>
<td>4%</td>
</tr>
<tr>
<td>Temperature</td>
<td>---</td>
<td>95%</td>
<td>5%</td>
</tr>
<tr>
<td>Oil Demand</td>
<td>26%</td>
<td>67%</td>
<td>7%</td>
</tr>
<tr>
<td>Temperature</td>
<td>---</td>
<td>93%</td>
<td>7%</td>
</tr>
</tbody>
</table>

Coal vs Temperature: \( r = -0.64 \) (\( r^2 = 41\% \))

Oil vs Temperature: \( r = -0.80 \) (\( r^2 = 64\% \))
Table 3.1 also includes the raw cross correlations of demand and temperature, to provide us with an initial indication of sensitivity, and to be elaborated later. To supplement these latter, a scatterplot of raw monthly oil demand on temperature is given in Figure 3.2a. Clearly, the overall relation is unambiguously linear.

Since it is necessary to isolate the temperature dependent component of demand, several anomalous values, which were not weather induced, also had to be removed. Such a complication arose in connection with the coal miners' strikes of winter 1972 and 1974. The anomalously low values of Jan to Apr 1972 and Jan to Mar 1974 were replaced by more realistic monthly trend values. These were obtained by fitting a least squares polynomial curve. Clearly, the atmosphere never goes on strike and does not therefore require any such adjustments. Also, the seasonal effect does not increase with the mean (Figure 3.1), i.e. there is no undesirable heteroscedasticity and therefore a logarithmic transformation to make the seasonal effect additive is superfluous. The data base is now ready for analysis.

3.5. THE TEMPERATURE CORRECTION MODEL

The technique of arriving at the temperature dependence and hence the TCF's was to remove trend ("detrend") and seasonality ("deseasonalise"), so as to reduce the series to stationarity. In more detail, the procedure devised was as follows:

1) seasonally adjust (deseasonalise) the raw monthly demand and temperature;
2) take deviations of deseasonalised demand from a trend (linearly interpolated between annual means, see later);
3) take deviations of deseasonalised temperature from the mean temperature for the period);
4) cross correlate the demand deviations (DDEV) with the temperature deviations (TDEV);
5) hence obtain a linear regression representing intra-seasonal sensitivity; and finally
6) express demand deviations per unit deg C as a percentage of raw data to obtain the TCF's.
Figure 3.2:  
(a) A scatterplot of raw oil consumption on temperature.  
(b) The multiplicative seasonal factors for demand and temperature (see also Table 3.2).
3.5.1. REMOVAL OF SEASONALITY (DESEASONALISATION)

The raw energy and temperature data possess a high degree of serial correlation or persistence. This is mostly due to seasonality but also, in the case of demand, to trend. The annual cycle therefore now needs to be eliminated. Various methods are available for seasonal adjustment ranging from the straightforward to the very advanced. These include % deviations from monthly means, 12-point moving averages or the more complex Census Bureau "X11" program used by DoE. The author has used X11 at the Department of Energy, and several other schemes were also attempted but suffered from various interpretation problems. The method used here was chosen for its lack of constraints on interpretation and for its general applicability to series of different time scales. For a more complete exposition of alternative methods, see Kendall (1973).

The data were deseasonalised by, firstly, dividing the monthly values by the annual mean for that year. This yields "seasonal factors" which are >1 in winter and <1 in summer. Mean seasonal factors for all Januarys, all Februarys, etc, were then computed. Finally, the raw data were divided by the mean seasonal factor appropriate to that month. This has the effect of boosting up summer demands and depressing winter demands. Thus the seasonal wave is eliminated. These multiplicative mean seasonal factors, for coal as an example, are shown in Table 3.2.

Table 3.2: The multiplicative seasonal factors for coal and temperature; see also Figure 3.2b.

<table>
<thead>
<tr>
<th></th>
<th>Coal</th>
<th>Temp</th>
</tr>
</thead>
<tbody>
<tr>
<td>Jan</td>
<td>1.15</td>
<td>0.43</td>
</tr>
<tr>
<td>Feb</td>
<td>1.17</td>
<td>0.45</td>
</tr>
<tr>
<td>Mar</td>
<td>1.13</td>
<td>0.57</td>
</tr>
<tr>
<td>Apr</td>
<td>1.02</td>
<td>0.80</td>
</tr>
<tr>
<td>May</td>
<td>0.98</td>
<td>1.12</td>
</tr>
<tr>
<td>Jun</td>
<td>0.88</td>
<td>1.46</td>
</tr>
<tr>
<td>Jul</td>
<td>0.83</td>
<td>1.63</td>
</tr>
<tr>
<td>Aug</td>
<td>0.75</td>
<td>1.66</td>
</tr>
<tr>
<td>Sep</td>
<td>0.90</td>
<td>1.46</td>
</tr>
<tr>
<td>Oct</td>
<td>1.00</td>
<td>1.16</td>
</tr>
<tr>
<td>Nov</td>
<td>1.05</td>
<td>0.72</td>
</tr>
<tr>
<td>Dec</td>
<td>1.12</td>
<td>0.53</td>
</tr>
</tbody>
</table>
Those for oil, in addition to coal, are also shown graphically in Figure 3.2b. Hereafter in this Chapter, by "short-term" we will mean "inter-monthly" or "intra seasonal" ("intra" is "within", "inter" is "between").

The deseasonalised demand series are presented in Figure 3.3, together with a trend to be explained shortly. Clearly, the annual wave has now vanished, with only trend and irregulars (short term) remaining. The Acf's of raw and deseasonalised coal demand, and TDEV, are shown on Figure 3.4. That for detrended data (DDEV) is also shown, and will be examined soon. (The Acf's for coal and oil are almost identical, and the differences are sufficiently uninteresting to justify only coal being presented. This happens quite often throughout the analysis; single examples being presented as opposed to taking space for the sake of completeness).

Referring to Figure 3.4b, the annual cycle apparent in the raw series, as indicated by its Acf, has now completely vanished. Hence our seasonal adjustment method would appear to be totally satisfactory. There is still allot of persistence around, due to trend. The deseasonalised demand series (DES) is still not stationary. The deseasonalised temperatures (TDEV), being devoid of any initial trend, are already stationary after seasonal adjustment, as indicated by the TDEV Acf (Figure 3.4a). The trend in demand still requires removal. This leads us conveniently onto the next step in the development.

3.5.2. STEPWISE LINEAR TREND INTERPOLATION (DETRENDING)

The next step was to take deviations of deseasonalised data from the overall general trend (i.e. detrending). A stepwise linear interpolation technique was derived here to identify this trend and allow its separation. It will be much used throughout the thesis and will be fully justified later in the context of finer scale data. The method is a whole subject in itself; suffice it to say at this stage that it performs very well. Other methods could have been chosen and indeed were experimented with but were felt inappropriate here (Chapter 2).
Figure 3.3: The deseasonalised coal and oil series, together with the stepwise linearly interpolated trends.
Figure 3.4:  
a) The autocorrelation function of TDEV (for coal).  

b) The acfs for the raw, deseasonalised and residual coal series (the horizontal lines are the 95% confidence bands for lag r described in Chapter 2.
In this scheme, individual monthly trend values are interpolated linearly between the annual means of deseasonalised demand, taking the annual means as being representative of the mid point of each year (July 1). The equation used to compute trend values for the demand series in this way was:

\[ \text{TREND} = \text{YM1} - \text{NM} \times (\text{YM1} - \text{YM2})/12 \tag{3.1} \]

where: YM = annual mean, NM = number of month(1..12)

The deviations of deseasonalised demand from this trend will be termed residuals or demand deviations (DDEV). These may now be cross correlated with deseasonalised (and implicitly detrended, since we subtracted the constant mean) temperature (i.e. temperature deviations, TDEV).

Because this method takes each year's mid point as the boundaries for each intervening interpolation, it cannot initially calculate trend values for the first or last 6 months. It became necessary, as a consequence, to compute fictitious annual means for the year preceding the first and following the last. This was achieved by linear extrapolation backwards from the first 2 annual means and forwards from the last 2 respectively. Equation (3.1) could then be applied as before.

Figure 3.3 shows the trends fitted to the seasonally adjusted data; clearly they provide an accurate representation of inter annual trend, by definition. Similarly, the approach succeeds in removing almost all the persistence, as will now be demonstrated.

3.6. RANDOMNESS TESTS ON RESIDUALS

The residual series (deviations) will now be tested for persistence/randomness, to establish the validity of the forthcoming cross correlations. The deviations themselves (DDEV, TDEV) are given in Figure 3.5; only coal is shown since oil is so similar, and the TDEV series partly overlap
Figure 3.8: The residual (detrainled and deseasonalised) coal and temperature.
temporally in any case. The Acf's for coal DDEV, and TDEV for coal, were shown in Figure 3.4b. The serial correlation originally present in the deseasonalised series has now almost vanished on detrending, though there is still some very short term persistence out to a lag of about one month, after which the Acf dampens down rapidly. This is also true for temperature (Figure 3.4a), this physically means that a month colder than average for the time of year tends to be followed by a further colder month, on average.

Turning now to the correlogram test of randomness described in Chapter 2, slightly over 5% of lag r's fall outside +/-1.96\sigma/N, for both DDEV and TDEV (Figure 3.4). The series are therefore not quite stochastic white noise sequences. Furthermore, there is a slight peak in the Acf at a lag of 12 and integer multiples thereof. The seasonal effect has not been completely removed, a problem common to all methods of removing quasi predictable cycles with an exactly periodic function (seasonal factors in this case, Figure 3.2b). For our purposes, since there is so little persistence and the cycle is so weak, we can regard the residuals as approximately stationary. The implied number of independent values (n) will, as always in this study, be used in significance testing, and these are given below.

| Table 3.3: Persistence statistics for the residual series. |
|---------------|-----|-----|-----|
|              | N   | ENR | n   |
| DDEV (Coal)  | 144 | 2   | 48  |
| TDEV         | 144 | 2   | 48  |
| DDEV (Oil)   | 156 | 2   | 52  |
| TDEV         | 156 | 2   | 52  |

One would expect some short term serial correlation in consumption as well as temperature. This arises from the general inertia in the response system, which is especially marked here since we are dealing with deliveries and therefore fuel storage. Another important reason why there is any autocorrelation in DDEV at all, becomes clear when
one considers inertia in \( TDEV \). It appears that at least part of the persistence in intra seasonal demand (as represented in \( DDEV \)) could be being forced by persistence in \( TDEV \) (as suggested by the relative lag times of \( DDEV \) and \( TDEV \)). It could also possibly result from a lag or delay in consumer response to \( TDEV \) (detailed later). This apparent sluggishness in reaction, as reflected by persistence, will crop up repeatedly later. To supplement this theory, it will be demonstrated later that a significant cross correlation exists between \( DDEV \) and previous month's \( TDEV \).

3.7. THE TEMPERATURE CORRECTION FACTORS.

A linear regression was then performed on the residual series, yielding the following basic equation, with various refinements to be explained shortly:

\[
DDEV = a + b \cdot TDEV + \text{error} \tag{3.2}
\]

where: \( a \) is a small constant; \( b \) is slope parameter.

The error term is the "residual error" (actual - predicted demand, Chapter 2), and though always included, explicit identification of it will hereafter be omitted.

The slope parameter represents the (average) sensitivity to \( TDEV \), i.e. demand deviations for every 1 deg C \( TDEV \). It becomes the TCF when expressed as a % of raw demand:

\[
TCF = \frac{b}{\text{RAW}} \times 100 \% \tag{3.3}
\]

The TCF may then be used to temperature-correct or deweight the raw consumption using:

\[
TCS = \text{RAW} - b \cdot TDEV \tag{3.4}
\]

where: \( TCS \) = temperature corrected series.

The results will now be shown, interpreted and critically discussed.
3.8. RESULTS AND INTERPRETATION

3.8.1. GENERAL TEMPERATURE SENSITIVITY OF RESIDUALS

The following table summarises the cross correlations of the residuals, and the relevant statistics introduced in Chapter 2.

Table 3.4: Cross correlations of the residuals (DDEV vs TDEV) and associated statistics

<table>
<thead>
<tr>
<th></th>
<th>r</th>
<th>r^2</th>
<th>t</th>
<th>a</th>
<th>b</th>
<th>SE(b)</th>
<th>TCF</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coal</td>
<td>-0.52</td>
<td>27%</td>
<td>7.3</td>
<td>21</td>
<td>-166</td>
<td>23</td>
<td>1.41%</td>
</tr>
<tr>
<td>Oil</td>
<td>-0.24</td>
<td>6%</td>
<td>3.0</td>
<td>3</td>
<td>-57</td>
<td>19</td>
<td>0.52%</td>
</tr>
</tbody>
</table>

where: a and b are regression coefficients,

SE(b) is standard error of b.

The first point of interest to note is that the residual correlations are lower than those with raw data (compare Table 3.1), especially for oil. This indicates that a large proportion of the original (raw) temperature dependence was attributable to seasonality. The residual regressions are still highly significant (>99%) and represent the short term (inter monthly) sensitivity. Though statistically significant, those for oil particularly are poor.

As anticipated, the value of a (the intercept) is small, i.e. there is little DDEV for zero TDEV. For both coal and oil there is a demand rise of the order of 1% for each TDEV fall of 1 deg C (about 50-150,000 tons, as indicated by the slope parameter b).

It was hypothesised from persistence considerations that fuel consumption could also be related to previous month’s TDEV. This is especially reasonable here, for consumption is defined in terms of deliveries, e.g. deliveries might be greater after a cold month. This hypothesis was tested by regressing DDEV on TDEV lagged one month (DDEV(j) vs (TDEV(j-1)), where j is month). The
resulting correlations were $r = -0.39$ and $-0.19$ for coal and oil. Though poor, these are not only significant at $>95\%$, but they are of comparable magnitude to $DDEV(j) \text{ vs } TDEV(j)$. Hence there could conceivably be a lag in reaction on this time scale (e.g. via fuel storage), though this could also be a manifestation of persistence in $TDEV$.

So, even on a coarse time and space scale, there is sensitivity to present and (possibly) past weather. This provides us with the first hint at the importance of lag effects and inertia in general. It suggests that on finer time scales some combination of past and present temperature may prove useful.

Returning to regressions on present month’s $TDEV$, the residual correlations, though statistically significant, are low. This raises doubt about the validity of an average $b$ and hence the TCF itself. To illustrate this, it was instructive to compute the standard error of $b$ (Table 3.4), and therefore the 95% confidence bands for the average TCF’s. The following results show such 95% bands for $b$ to be rather wide and hence those for TCF are not at all firm.

Table 3.5: The 95% confidence bands for $b$ and TCF.

<table>
<thead>
<tr>
<th></th>
<th>$\hat{b}$ $\pm$ SE($b$)</th>
<th>TCF $\pm$ 1.96*SE($b$)/√ RAW</th>
</tr>
</thead>
<tbody>
<tr>
<td>coal</td>
<td>$\hat{b} = -166 \pm 45$</td>
<td>TCF $= 1.41% \pm 0.38%$</td>
</tr>
<tr>
<td>oil</td>
<td>$\hat{b} = -57 \pm 37$</td>
<td>TCF $= 0.52% \pm 0.34%$</td>
</tr>
</tbody>
</table>

where: "$\hat{\text{ }}$" refers to “estimate of population parameter”
"$\gg$" means “which implies”

3.8.2 SEASONAL VARIATIONS IN SENSITIVITY

An interesting aspect of this model as a whole is that the TCF’s (like $b$) are a measure of consumer sensitivity to temperature. We would perhaps expect this to vary through the year. In an attempt to uncover this, separate monthly regressions were performed and the results are now summarised in tabular form.
Table 3.6 shows that the sensitivity is higher at certain times of years than at others. Though the variation between months is highly significant (at >99%), this pattern is very erratic. The following illustration depicts this seasonal variation graphically.
Figure 3.6 shows that with the exception of the October peak, there is no correspondence between the coal and oil monthly slope parameters. The series appear to be random. The coincidence of the October maximum could be due to effects of small sampling.

A drawback of this technique is that each monthly regression is performed on only 12 (or 13 for oil) pairs of DDEV, TDEV values. In a similar way, separate annual correlations were performed but suffered from the same problems. The interannual variability was even more erratic, and the results are not worth either presenting or commenting on.

In either case (seasonal or annual regressions), such small samples may lead to unrepresentative correlations, although the t test, used in testing their significance, takes into account sample size (equation 2.6). In any case, the standard errors and confidence bands are so broad as to render intermonthly comparisons not very useful. It might be interesting to calculate quarterly TCF's but again there are interpretation problems. There seems little point, as a result, in pursuing any physical interpretation. Further errors and spuriousness will be introduced by, for example, some commercial companies having contracts for only quarterly deliveries. If such a delivery happens to coincide with a cold month, the monthly slope parameter will be forced to be unrealistically high. At other times the effects may tend to counteract.

The results of the monthly residual cross correlations should only be taken as a very general indication of consumer response. The overall (whole data set) residual correlations are still useful in a somewhat broader sense. It would seem appropriate and natural here for this discussion to lead into a consideration of the model's problems as a whole, in addition to specific statistical assumptions and inferences, and so to conclude the discussion.
3.9. CONCLUSIONS AND PROBLEMS

A statistically significant relation has been found between both raw and detrended/deseasonalised demand, and temperature. The previous month’s temperature was also shown to be significant; i.e. the possibility of a lag or inertia was identified. However, physical interpretation has proved to be difficult. It was stated at the outset that the nature of the data, its time and space scale, etc. has limited the usefulness of the model. It was also stated that a critical evaluation would be undertaken. Throughout the course of the discussion, a number of problems were considered as they arose in the context of the derivation. Some further criticisms, in addition, need to be levelled at certain areas. These will now be detailed, and indications will be made, wherever possible, as to possible solutions.

1) The data are of coarse time and space scale; this will limit the model’s applicability. Also, the data are contaminated by various non-weather effects.

2) The temperatures are spatial averages of 15 spot values; these may not be statistically representative of the regional variation of demand. Investigation of various spatial weighting schemes could possibly prove useful. The resulting variations between different areal averages are likely to be small, since the data are polluted by so many other non-temperature-dependent influences.

3) Because the data is aggregated, the model formulation assumes that consumer response is spatially uniform. This problem of aggregation will also be discussed later.

4) Demand levels are influenced by many economic and political factors such as fuel price variations, Government policies, etc. Hence the correlations are rather poor. As many of these factors as possible should be incorporated into trend and seasonality.

5) Consumption is affected by other meteorological variables, such as windspeed and sunshine, though on this scale these would be spatially and temporally smoothed out.

6) Errors will arise due to storage of fuels, remembering the data were deliveries (sales).
7) Coal and oil are used for other purposes besides the weather sensitive domestic heating. These include industry, transport and commerce, as detailed in Section 3.3, see also Appendix 1. Once again, this leads to high residuals. There are no consumption data for specified end-uses but separate deliveries data for domestic coal are available (Department of Energy) and these would perhaps be expected to be more temperature dependent. This was tested. Monthly Domestic Coal deliveries were obtained from "Energy Trends" (DoE) for the 6 year period 1976-81. This sub-sector comprises "House Coal" + "Other", where "Other" includes miners coal, anthracite and dry steam coal. Once again, statistical (4/4/5-week) months were converted or normalised to calendar months. Contrary to expectations, the correlations were lower: \( r = -0.38 \) and \( +0.08 \), for raw and residual regressions respectively. This is possibly because such data included non weather-sensitive and non seasonally varying coal types, but could also result from much smaller sample size.

B) A combination of an additive and multiplicative formulation, of trend and seasonality respectively, was assumed. Many other schemes were attempted, with disappointing results.

9) The raw temperatures are monthly averages. This may tend to smooth out any non-linear reaction there may be to temperature. Furthermore, individual sensitivity to temperature is probably linear up to some critical temperature, with zero sensitivity above (detailed later). Degree days would at first sight appear to overcome this, though at the national level it assumes that a realistic average base temperature for the entire population can be established. Further reasons for discrediting heating degree days were debated in Chapter 1.

10) Other methods of detrending and deseasonalising could have been used, but were abandoned.

11) The presence of persistence is an important central problem. Several research strategies for dealing with it were put forward in Chapter 2, and were applied here with encouraging results.

12) Care should be taken in not mistaking apparent
correlations, such as some of the monthly regressions, for real, genetic (cause effect) ones, especially since these are small samples with few independent values. In process-response relations, causal mechanisms such as temperature affecting fuel usage should be cautiously inferred.

13) The discovery of a possible lag of response to temperature, even on this coarse scale, points to the need for its further examination on finer time and space scales.

The study has therefore highlighted some of the difficulties involved in weather-demand analysis, especially with coarse data. The nature of the data has quite severely limited the usefulness of the results, which should therefore be taken only as a broad indication of customer response. Physical interpretation has so far been hindered by ambiguities arising from the statistical techniques. This problem will become progressively less significant as we consider finer time scales. This is why it was necessary to commence at this scale, despite being somewhat low key (in some senses), in relation to later Chapters that is.

Despite some of the results being somewhat negative, some success has been achieved in identifying the overall scale and nature of short term (intra seasonal) sensitivity of coal and oil usage patterns. Having paved the way partially, we may now proceed to a finer time and space scale.
CHAPTER 4

MODELLING WEEKLY GAS AND OIL DEMAND AT EDINBURGH UNIVERSITY: A LOCAL CASE STUDY

4.1. INTRODUCTORY COMMENTS

The previous Chapter has shown that the consumption of fuel for purposes such as heating is, as expected, controlled by temperature. The nature and importance of this control are very much dependent on the selection of time and space scale. In most cases, an increase of space scale tends to smooth out individual demand–weather responses. We have just seen this at the national level with monthly coal and oil data. Under such circumstances, these reactions are often still in evidence in a more gross or aggregate way (as indeed they were). On the contrary, a decrease of scale often uncovers them. Two separate campuses at Edinburgh University provide a particularly interesting illustration of the latter.

This Chapter summarises the results of an investigation of weekly gas and oil demand, for two individual groups of buildings. These are King's Buildings and Medical Buildings at Edinburgh University, hereafter simply referred to as "KB" and "MB" respectively. This is an ideal space scale to start to understand the effects of local atmospheric conditions and microclimate on local fuel usage. Here, we define "local scale" to mean an individual building or group of buildings. It is, after all, many thousands of micro-scale responses that make up the regional total (which follows this Chapter). This is one of the most important and interesting applications of local case studies. Since the time scale has now reduced, it becomes possible to detect the effects of solar radiation and windspeed, in addition to temperature.

Having modelled such effects, such data are very useful for demand forecasting, though with weekly data this can only be carried out on a very general basis. This Chapter is not, as a consequence, intended as a demand
forecasting tool (discussed later). Sources of error in the data, defects and merits of the models, and so forth, will be presented as appropriate in each Section. The approach sets out to further demonstrate the usefulness of meteorological data, and at this scale we are beginning to find something out about short term response. On this weekly time scale, by "short term" we mean "inter weekly" (i.e. "intra seasonal"). These weekly data do still smooth out temporally short reactions. These and other problems are discussed and some consideration is given to difficulties arising when data are contaminated by various effects. This Chapter also highlights the problems ensuing when fuel is used for non weather-sensitive sub-sectors (i.e. besides domestic space heating).

This choice of scale is additionally interesting from an energy conservation viewpoint, using meteorological data. As such, it contains in the final Section a useful money saving application of weather-demand modelling to a real practical management problem - that of rearranging University terms and vacations to save fuel. The approach used in this phase of the work has important industrial and domestic applications in energy conservation management.

Before proceeding any further, it is important to stress that Edinburgh University is very special or peculiar in terms of its load-mix characteristics, and in its weather sensitivity. An integral feature of the fuel management system is that the energy usage is centrally dictated (actually by computer, see later). This high degree of centralised control means that individual weather sensitivity (people turning fires on) is lost, though overall responses are still obvious. These points should be borne in mind in considering the nature of the data, since they feed through to or propagate errors into the data itself. Nevertheless, this scale is very illuminating for several reasons to be detailed, and its consideration is important in appreciating regional daily patterns in Chapters 5 and 6. This is how it fits into the context of the thesis as a whole.
4.2. THE DATA SETS

4.2.1. THE ENERGY DATA BASE

The energy data base comprises weekly totals of gas consumption at Medical Buildings and oil consumption at King's Buildings. Both are in 100 litres, and are from September 1976 to July 1978 (almost two years). These weekly totals were meter-read manually direct from the boiler houses concerned. For convenience, the period is divided into two 49-week stretches which, though temporally contiguous, represent two administratively distinct "years". KB and MB were treated separately in the analyses. The resulting four data sets will be referred to as follows:

Year 1: Sept 12, 1976-Aug 14, 1977: referred to as "KB1", "MB1"
Year 2: Aug 21, 1977-July 23, 1978: referred to as "KB2", "MB2"

Note that these dates refer to "week beginning". Note too that here we are now dealing with actual consumption and not deliveries. We will therefore be getting closer to the real underlying nature of sensitivity, and the assumption of demand being synonymous with consumption now becomes more realistic.

The raw demand data are presented graphically in Figures 4.1 and 4.2, together with temperature, to be explained shortly. Once more, the annual cycle is in evidence. The anomalous effects of Christmas and Summer vacations are also clear. It is a feature of the energy management set-up at Edinburgh that heating loads are off over these vacations. It is relevant to the interpretation of these profiles to consider some further aspects of the management. This will be pursued in Section 4.3, after introducing the meteorological data.

4.2.2. THE WEATHER DATA BASE

The corresponding meteorological data consist of weekly mean temperatures, windspeeds, and sunshine hours at Bush Estate. These are instrumental measurements taken at a "standard" site. Bush is 4 miles South of KB. It is
Figure 4.1: The raw weekly consumption profiles for KB1 oil and MB1 gas; together with the synchronous weekly temperatures: Sept 1976-Aug 1977.
Figure 4.2: The raw demand for KB2 oil and MB2 gas demand, Aug 1977-Jul 1978, and corresponding weekly mean temperatures.
sufficiently close and similar to the University to be thought of as representative of conditions there.

The weekly mean temperatures were obtained from the daily average of maximum and minimum temperature. These weekly means are given in Figures 4.1 and 4.2, and clearly show seasonality. The weekly mean windspeeds (knots) were calculated from values of the hourly wind run. Because the wind run is continuous, and because of the diurnal variation in windspeed, lower (on average) overnight winds are included. Calms are more common at night, due to the diurnal cycle in boundary layer turbulence. The problems that this introduces will be discussed later. Weekly sunshine hours are unambiguous. Hereafter, temperature, sunshine and windspeed will be referred to as T, S, and U.

The raw windspeed profile for Year 1 and sunshine for Year 2, are given in Figure 4.3. Sunshine in particular exhibits a fairly obvious seasonal variation, but the annual cycle in wind is somewhat less marked (though it is present). The other T, U and S traces are very similar.

Before discussing the statistical and physical properties of these data, we need to consider the fuel management system. We will then be in a better position to return to a more complete appreciation of the data itself.

4.3. THE ENERGY MANAGEMENT ORGANISATION

To gain a better physical interpretation of the data and results, a consideration of the fuel management organisation is relevant. Over the period considered, the boiler house at KB was fired by oil, and by gas at MB, from which vacuum steam was piped to individual buildings. This is then used for heating either by reduction back to water at some buildings or by steam heating elsewhere. This is the weather-sensitive component of demand.

Only weekend weather forecasts are at present used (and these only since September 1977). To this end, Scottish Gas supply weekend temperature forecasts (in broad bands) on a routine basis every Friday. These are especially useful for frost protection of certain buildings, and maintaining interior temperatures at specific levels, e.g. for animals.
Figure 4.3: The weekly mean windspeed (1976/77) and sunshine (1977/78) records for Bush Estate.
or some laboratory equipment. A certain amount of short-term sensitivity to the weather is also allowed if the boiler operator feels from experience that demand will increase due to sudden cold spells, etc. KB now use gas-fired boilers but retain an oil-fired boiler, since their contract with Scottish Gas allows an interruptable gas supply, forcing them to use oil temporarily.

In addition to heating, the fuel is used for several non weather sensitive sectors such as process steam, domestic hot water, cooking, laboratory equipment and 24-hour processes. Figures 4.1 and 4.2 reveal a fall in demand over summer, arising because the heating system is switched off from June to September. The remaining load at this time consists of the above components. At Christmas and New Year also the system closes down, hence the sharp trough in the otherwise high winter load levels.

These irregularities in the heating season have a polluting effect on the data. While being included in certain analyses, vacations will be removed for others, but this will always be indicated. Even though, clearly, the atmosphere does not have vacations, the corresponding (synchronous) weather data will also be removed on these occasions. Industrial disputes are another source of irregularity, though the smallness of their effect on weekly data means that the data are not seriously contaminated.

Another potential source of error is that arising from manual reading of meters. Boiler house staff perform this on a routine basis every week, but small variations in timing and accuracy may lead to errors. These are very difficult to assess, but one would expect them to be small in relation to the coarse scale weekly totals. A problem that will manifest itself concerns plant management. Since we are now at the microscale level, the high degree of load management sometimes tends to conceal the real underlying sensitivity.

A recently installed microprocessor is already in operation at KB, making the boiler house and remote plant completely automatic (or nearly so). There are several interesting features associated with this computerisation.

In some buildings there is an interior zoning system
which differentiates between south-facing offices, laboratory areas, lecture halls, etc. Such a system responds automatically to temperature sensors attached to interior walls. The present location of these sensors results in non-representative measures of interior microclimate and temperature levels. It is therefore problematical. The associated calculations of "warm up time", i.e. the run up (and run down) time in heating the buildings before (and after) occupation, are computerised and are performed in real time, of course. At present, the regulation of the heating plant at Edinburgh is closely tied up with a fuel conservation programme. Though this management system is still in its experimental stages, it is hoped that this form of energy control system will eventually (and satisfactorily) be entirely microcomputer-driven.

4.4. PHYSICAL AND STATISTICAL PROPERTIES OF THE DATA

4.4.1. SERIAL CORRELATION

The raw energy and weather data possess varying degrees of serial correlation, which are important to quantify. Once again, not all correlograms will be shown so as to save space. Those for temperature (Year 1) and KB2 oil demand are reproduced in Figure 4.4a and b. We have already noted the annual cycle from the raw traces. This induces serial correlation out to a lag of 7 and 10 weeks respectively for demand and temperature (Figure 4.4).

The correlogram of windspeed for Year 1 is given in Figure 4.4c. There is some short term (inter weekly) autocorrelation, out to a lag of about 1 week. The inclusion of lower overnight values (remembering U was derived from total wind run) is possibly having a distorting effect here. Nevertheless, there is still some persistence, probably due to a weak seasonal effect (windspeeds generally being greater in winter due to cyclonic activity, Figure 4.3). For Year 2, there is no persistence in U, but the differences are sufficiently uninteresting to warrant not showing this.

The sunshine correlogram for Year 2 is shown on Figure 4.4d. Here, the seasonal sunshine cycle is manifesting
Figure 4.4: The autocorrelation functions of:
a) Raw temperature (Year 1)  b) Raw KG2 demand
c) Windspeed (Year 1)         d) Sunshine (Year 2)
persistence of the order of 3 to 4 weeks. For Year 1 this becomes 1 week. This latter is surprisingly low, considering late summer 1976 was a drought period, though early summer 1977 was not as sunny, hence the annual cycle is weaker.

The following Table summarises these persistence statistics for future reference.

**Table 4.1: Persistence statistics for demand and weather data.**

<table>
<thead>
<tr>
<th>ENR</th>
<th>D</th>
</tr>
</thead>
<tbody>
<tr>
<td>Demand (KB2)</td>
<td>7</td>
</tr>
<tr>
<td>Temp (Year 1)</td>
<td>10</td>
</tr>
<tr>
<td>Wind (year 1)</td>
<td>2</td>
</tr>
<tr>
<td>Wind (year 2)</td>
<td>1</td>
</tr>
<tr>
<td>Sun (year 1)</td>
<td>2</td>
</tr>
<tr>
<td>Sun (year 2)</td>
<td>4</td>
</tr>
</tbody>
</table>

The remaining demand and temperature values are so similar as to not necessitate their reproduction.

### 4.4.2. MULTICOLLINEARITY

The meteorological variables were found to possess multicollinearity. The complete partial cross correlation matrices are given below.

**Table 4.2: Partial cross correlation matrices of T, U and S.**

\[
\begin{array}{ccc|ccc}
\text{YEAR 1} & & \text{YEAR 2} & & \\
T & U & S & T & U & S \\
\hline
T & 1.00 & -0.26 & 0.52 & T & 1.00 & -0.04 & 0.69 \\
U & -0.26 & 1.00 & -0.14 & U & -0.04 & 1.00 & -0.20 \\
S & 0.52 & -0.14 & 1.00 & S & 0.69 & -0.20 & 1.00 \\
\end{array}
\]

Those coefficients exceeding 0.53 are significant at 95%.

As expected, temperature and sunshine are positively correlated. The relationship between temperature and
windspeed is lost here, since we are dealing with weekly averages of both. The inclusion of lower overnight winds means that any short-term relations between U and T are smoothed out. Hence we have poor correlations for T with U. Sunshine and wind are poorly correlated to start with, on physical grounds (on this time scale at least).

4.5. LINEAR REGRESSION ANALYSIS

4.5.1. GENERAL WEATHER SENSITIVITY

The overall seasonality in temperature is obviously forcing that in demand. To uncover the gross or general effect that weather has on fuel consumption, raw demand was cross correlated with T, U and S, for each year separately. The results are now shown and will shortly be discussed.

Table 4.3: Weather-demand cross correlations.

<table>
<thead>
<tr>
<th></th>
<th>I</th>
<th>U</th>
<th>S</th>
</tr>
</thead>
<tbody>
<tr>
<td>KB1</td>
<td>-0.85</td>
<td>0.27</td>
<td>-0.55</td>
</tr>
<tr>
<td>KB2</td>
<td>-0.89</td>
<td>0.09</td>
<td>-0.67</td>
</tr>
<tr>
<td>MB1</td>
<td>-0.92</td>
<td>0.26</td>
<td>-0.42</td>
</tr>
<tr>
<td>MB2</td>
<td>-0.89</td>
<td>0.01</td>
<td>-0.68</td>
</tr>
</tbody>
</table>

Coefficients exceeding 0.53 are significant at 95%.
KB and MB both have very similar regression parameters for each year; the linear equations for KB2 and MB2 (arbitrarily) are reproduced below as examples. Demands are in 100 litres/week.

KB2 Oil     Dem = 1033 - 46 * Temp + error  \text{(4.1)}
MB2 Gas     Dem = 1609 - 82 * Temp + error

The slope parameters reflect the average response rate to temperature (100 litres/week/deg C). For KB and MB, these are on average about 6.5% and 8.1% of raw demand levels. It is interesting to note, as a corollary, that a 1 deg C drop in comfort levels/ heating requirement in University offices
would lower (the weather sensitive component of) fuel bills by >6%. This might be a useful statistic for energy conservation advertising campaigns.

Referring to Table 4.3, correlations of consumption with T appear highly significant, confirming the strong effect that temperature has on heating demand. Yet again we hypothesise that this is due to seasonality.

The high degree of inertia in the demand response system, due to seasonality, is supported by the fact that lag-cross-correlating demand with previous week's temperature gave r values exceeding 0.80. In this instance, since serial correlation in temperature is greater than that in demand, we cannot infer, from such highly significant lag cross correlations, the existence of a lag in response on this weekly time scale.

Considering wind, to average U over a week means that any short term links between U and demand are filtered out, resulting in poor correlations (Table 4.3). Sunshine correlates well with demand (95% level) suggesting, at first sight, that sunny weather enhances interior heating, especially for south-facing offices. Thus we are beginning to see the effects of interior microclimate on energy demand. Furthermore, for both groups of buildings, the strength of correlation of S on demand increases over the two years (90% significantly for MB, by Fisher's Z transformation). It is likely that for S with demand, the apparently quite high r values (Table 4.3) arise from the multicollinearity of T with S (Table 4.2), and from the seasonality of both.

This latter would appear to be a particularly good example of the care that needs to be exercised in inferring causal relationships between two variables. Apparent correlations such as these should not be mistaken for real genetic ones.

4.5.2. IMPROVEMENTS IN FUEL MANAGEMENT EFFICIENCY

Returning to temperature, so far it has been implicitly assumed here that the demand-temperature relation is linear. Scatter plots of T on demand have been
prepared to visually confirm (or otherwise) this expectation (Figure 4.5). Examination of these scatter-plots reveals the distorting effect that Christmas (for KB2) and Summer vacation have. Also, visually the anomalous Summer values cluster in the lower right. Inclusion of them would suggest a higher-order polynomial fit, though clearly the overall relation is almost linear. For KB2 there does seem to be some evidence (albeit very weak) of greater sensitivity at higher temperatures, suggested by the group of values marked A. For data of this time scale, this is probably not significant and it would be a mistake to attempt to incorporate this into such a best fit curve, for this application. In addition, there is no sign of demand saturation (decreasing sensitivity) at low temperatures.

More interestingly, visual comparison of the scatter-plots in Figure 4.5 shows considerably less scatter for Year 2 than Year 1. Table 4.3 also reveals r to improve over the 2 years. If vacations are omitted, this increase is even more obvious (and is significant at 90% in that case). This increase is also apparent for sunshine, as we have seen (Table 4.3). Here, then, statistical evidence (r) supports visual evidence (scatter).

This improvement could result from the improved fuel metering ("telemetry") introduced at KB in February 1978. It could additionally be due to the use of Meteorological Office weekend forecasts from September 1977 onwards. An increasing interest in energy conservation probably also led to greater awareness of energy personnel to weather events. It would seem that the fuel management system now responds more rapidly to the weather than in 1976/77. Hence the exercise was of interest, and was useful from the standpoint of physical interpretation with respect to fuel management. It demonstrates, as a corollary, that the cost savings made by the University in those 2 years were not (necessarily) achieved at the expense of personal comfort.

Once more (and finally), we suspect that most of the variance in demand is explained by seasonality. This annual cycle dominates the correlograms and induces autocorrelation. It must therefore be removed.
Figure 4.5: Scatterplots of raw KB oil consumption on weekly temperature, for both years.
4.6. THE DESEASONALISATION SCHEMES

Since most of the variance in demand (>80% as we shall see) is explained by seasonality, this is disguising any short term (inter weekly) response that may be present. A periodogram is hardly necessary here to display this dominance. The seasonality in demand is partly temperature dependent in itself but is also due to the composition of the University year (terms, vacations, etc). On this time scale, seasonality was removed in 2 ways:
1) To fit a least squares sine wave to the raw demand and temperature series (equivalent to wavenumber one), thence to take deviations from it;
2) To first-order difference the demands and temperatures.

Other methods could have been selected but were discarded. For a comprehensive discussion of these, see Chapter 2. Deseasonalisation will be very useful, since then we can quantify the importance of the seasonal effect, and identify the scale and nature of inter weekly sensitivity (if there is any). We will commence with the spectral approach.

4.6.1. FOURIER (SPECTRAL) DECOMPOSITION

Though the harmonic approach was discredited for various reasons in Chapter 2, it is the most applicable method of seasonal adjustment in this context. This is true because there turns out to be almost no residual persistence in this instance. This means that it does not overlook short term (inter weekly) variability. Also, the stepwise interpolation method used in Chapter 3 is not suitable here because of the time scale and length of the data base. The sine fit provides a convenient physical basis here, and will be justified accordingly.

The least squares sine waves, obtained by Fourier decomposition, were fitted to the demand and temperature series. The shortened (39-week, vacations omitted) records are used in this part of the analysis because inclusion of shutdowns would introduce harmful spurious cross correlations into the deviations. The wavenumber one curves are all very similar, that for KB2 is given in Figure 4.6a.
Figure 4.6:  

a) The harmonic fit to the annual cycle (KB2)  
b) The KB2 demand deviations  
c) The correlogram of the KB2 residuals.
Clearly, it provides a visually good overall fit, explaining >80% of raw variance in all cases. The deviations therefrom (residuals) will be examined shortly.

4.6.2. FIRST-ORDER DIFFERENCING

A computationally convenient method of treating seasonality (and, indeed, trend if need be), is to replace each value in a record by the difference between itself and its predecessor. This is termed "first order differencing" and has not been used in this study thus far, apart from a brief mention in Chapter 2. The first order (backward) differenced value is then given by, with obvious notation:

\[ \text{Dif}(t) = x(t) - x(t-1) \]  

where: \( t \) is time and \( x(t) \) are original values.

Clearly, an end-point is lost in the process. Many varieties are available, such as forward- or centred differences, or leap-frog versions, and this area forms an important part of numerical modelling (time stepping), amongst other fields. It is used to represent finite difference approximations to continuous derivatives in time or space. Box and Jenkins (1970) stress its importance in time series analysis. In this context, it is really a special kind of smoother. Any order of difference can be taken; this is helpful if there are cycles present. For instance, in the daily electricity demand data in Chapter 2, we could have used seventh order differencing to remove the weekly wave.

The idea is to difference a record until it becomes stationary. For our purposes, it will only need to be applied once to attain stationarity. One should be wary of the effects of taking repeated differences of the same trace. First order differencing will be applied to both demand and temperature, so that the differenced series may then be cross correlated. This will be very helpful here, for the differenced traces should show no trend, seasonality or periodicity at all. This will render any cross correlations at their most meaningful and significant.

*First-order differencing will tend to dampen the annual cycle when the variance associated with other temporal components is large.*
The spectral and differencing methods both leave us with residual series, which may be cross correlated for short term dependence. Firstly (as always in this study) they must be tested for randomness.

4.7 TESTS OF RANDOMNESS ON RESIDUALS

The deviations from the sine wave, for KB2 as an example, are presented in Figure 4.6, with the Acf. All residual series are visually very similar. The residual trace shows the existence of very short term local trends.

The correlogram test of stationarity indicates very weak serial correlation effects, out to a lag of about 1 week (beyond which the Acf quickly dampens down), Figure 4.6. Both these points suggest that the record is not quite random. All other residual series (not shown here), including temperature, were found to be random. Since the temperature residuals show no persistence, we cannot necessarily assume, on this occasion, that the short term persistence in demand is being forced by persistence in temperature. We suspect, however, that the KB2 deviations are very close to being stationary, and therefore we need a further test to supplement this one.

There are 13 turning points on the KB2 residual trace (Figure 4.6b). Compared to an expected 26 turning points if random, they are clearly not stochastic white noise. All other residual records were random on all these criteria.

The number of turning points for all the residual series are now tabulated:

<table>
<thead>
<tr>
<th></th>
<th>Expected (if random)</th>
<th>Actual</th>
</tr>
</thead>
<tbody>
<tr>
<td>KB1DEV</td>
<td>26</td>
<td>13</td>
</tr>
<tr>
<td>KB2DEV</td>
<td>26</td>
<td>25</td>
</tr>
<tr>
<td>MB1DEV</td>
<td>26</td>
<td>25</td>
</tr>
<tr>
<td>MB2DEV</td>
<td>26</td>
<td>25</td>
</tr>
<tr>
<td>All DIF series</td>
<td>32</td>
<td>30</td>
</tr>
</tbody>
</table>
First-order differencing also generated a residual series. Again these are all very similar; that for KB1 is reproduced in Figure 4.7, with the Acf and this time with its wave spectrum too. Typically for a differenced series, and interestingly so, it possesses alternating local maxima and minima. This is a manifestation of "negative persistence", where a value tends to be followed by a value opposite in sign. This is in striking contrast to the more normal positive persistence cases already encountered. As a result its correlogram also alternates, and starts with "negative" serial correlation at lag 1.

The turning points test (see Table 4.4), together with the fact that >95% of the Acf falls within \( +/1.96\sqrt{N} \) (see Figure 4.7), confirms that the differenced traces are purely random. Hence the differencing technique has successfully deseasonalised the series, by reducing them to stochastic white noise. To confirm this, the differenced KB1 series was put through a spectral analysis. Its periodogram is given in Figure 4.7, and clearly exhibits no proponderence of any particular wavenumber, apart from wave 24. This merely reflects the alternating nature of these 48-week differenced series (Figure 4.7), 48 since an end-point is lost.

Though differencing is remarkable in that it completely overcomes any problems, it does suffer here from interpretation difficulties. By differencing, what have we taken away, physically? Likewise, what is the physical significance of what's left? These are difficult to answer, and physical interpretation of the residual cross correlations becomes subjective.
Figure 4.7: The differenced series for KBI, accompanied by its correlogram and periodogram.
4.8 SHORT-TERM (INTER-WEEKLY) WEATHER SENSITIVITY

All residual series, both differenced and deviations, can be taken as quasi stationary. It is now appropriate to cross correlate, firstly, the deviations from the sine curve (wave one), to obtain the non seasonal sensitivity.

Table 4.5: Cross correlations of demand deviations from wave-number one with temperature deviations therefrom.

<table>
<thead>
<tr>
<th></th>
<th>ENR</th>
<th>t</th>
<th>Significance</th>
</tr>
</thead>
<tbody>
<tr>
<td>KB1</td>
<td>0.03</td>
<td>24</td>
<td>0.18</td>
</tr>
<tr>
<td>KB2</td>
<td>-0.64</td>
<td>16</td>
<td>5.07</td>
</tr>
<tr>
<td>MB1</td>
<td>-0.22</td>
<td>24</td>
<td>1.37</td>
</tr>
<tr>
<td>MB2</td>
<td>-0.50</td>
<td>24</td>
<td>3.51</td>
</tr>
</tbody>
</table>

By comparison with Table 4.3, it would appear that a significant part of the original raw temperature dependence was short-term (intra-seasonal). It was not all seasonal, as was hypothesised. In addition, the sensitivity (this time, short term) again increases significantly over the 2 years, especially for KB. This again could be a consequence of more efficient plant management at KB in the way discussed earlier.

The results of regressing differenced demand on differenced temperature are shown in the following Table.

Table 4.6: Results of the regressions of the differenced series.

<table>
<thead>
<tr>
<th></th>
<th>ENR</th>
<th>t</th>
<th>Significance</th>
</tr>
</thead>
<tbody>
<tr>
<td>KB1</td>
<td>-0.21</td>
<td>24</td>
<td>1.46</td>
</tr>
<tr>
<td>KB2</td>
<td>-0.57</td>
<td>24</td>
<td>4.71</td>
</tr>
<tr>
<td>MB1</td>
<td>-0.29</td>
<td>24</td>
<td>2.06</td>
</tr>
<tr>
<td>MB2</td>
<td>-0.35</td>
<td>24</td>
<td>2.53</td>
</tr>
</tbody>
</table>

The results are encouragingly and surprisingly similar to the harmonic residual cross correlations, both in the existence of and the general strength of inter weekly
response, and its increase over the 2 years. This perhaps has implications for short term sensitivity, but exactly how is far from clear. The reasons for such an underlying similarity are probably very subtle. The use of two different schemes thus proved very rewarding in this instance, and can be useful in similar sensitivity experiments on other scales.

So much for temperature; what about windspeed and sunshine?

4.9. MULTIVARIATE SCHEMES OF TEMPERATURE, WIND AND SUNSHINE

So, we have uncovered significant seasonal and short term sensitivity to temperature, as well as significant partial cross correlations between demand, sunshine, windspeed and temperature. How do they all act together? In the real world, all weather variables act in combination to produce an overall hybrid effect on energy usage. Chapter 2 explained the usefulness of the multivariate approach to ascertain this. A stepwise multiple regression analysis will now be performed, regressing consumption on temperature, sunshine and windspeed in that order (i.e. in the order of the importance of their individual partial correlations on demand). The multivariate model is given by:

\[
\text{Dem} = a + b*T + c*S + d*U + \text{error} \quad (4.3)
\]

where: \( a, b, c, d \) are partial regression coefficients;
\( t \) is time; \( T, U, S \) are weekly weather variables

In all four demand cases, the increase in \( r^2 \) (\% variance explained), when adding in \( S \) and \( U \), was <1.5%. At first thought, this would seem to contradict the significant partial correlations of \( S \) and \( U \) with demand. The reason for so little an increase lies in the multicollinearity of \( T, U \) and \( S \). It is apparently, therefore, not worth involving \( S \) and \( U \) in the model. Hence the simplest model, i.e. one relating consumption to temperature only, is just as satisfactory here.

The presence of multicollinearity has thus proved to
be a problem. Because the meteorological parameters are correlated between themselves, the multivariate approach is rendered useful in only a general way here, though later it will turn out to be indispensable.

4.10. ENERGY CONSERVATION APPLICATIONS

4.10.1. RESCHEDULING UNIVERSITY TERMS: A FEASIBILITY STUDY

At Edinburgh University there is an active and partially successful energy conservation program in operation. Since the heating plant was put onto microprocessor control in Autumn 1981, considerable savings have been achieved. The implementation and expansion of the system have gone hand in hand with improved telemetry (metering in individual buildings) at both sites.

The Fuel Conservation Committee is a body set up to investigate future ways of economising on fuel usage in all sectors. One possible way of realising such savings is to reschedule building occupancy patterns by re-organising the timings of terms and vacations. The point has already been made that the heating plant closes down at Xmas and Summer. Because Xmas lies in the depths of the heating season, this shutdown is much more noticeable on the demand profiles than the Summer vacation (Figures 4.1 and 4.2). Obviously, to close down the system saves money. It seems sensible to entertain the possibility of shutdown for an extra week at Xmas, and a compensatory extra week of term time at the end of the Summer vacation (October). That is, Autumn term would start and finish one week earlier. One would expect fuel to be saved at Xmas (being colder), when more energy is used to heat the University.

One would hope, naturally, that the saving at Xmas would exceed the extra heat needed for an additional week in October. We would expect this to be the case since October is warmer. To arrive at a general order of magnitude of the potential saving, various simplifying assumptions will be made. We only have 2 years data, so any results relate only to those years, and not in general. We will consider closing down the week beginning 18 Dec, i.e. the week normally
preceeding the present shutdown. The extra week will be that
beginning 3 Oct. We are therefore moving the term one week
back.

What then is the average saving we could hope to
achieve at Xmas? This would be given by the difference
between the average cost of heating for the extra Xmas week
and the average Xmas vacation load. The average vacation
load can easily be calculated (though only for 2 years
here). The average heating load for 18 Dec week is best
arrived at by using our previously defined linear regression
model (Section 4.5). If we denote this average load for the
time of year (if this week was in term time) by "SNAD" for
"seasonal normal actual demand", then the saving would be
given by, with obvious notation:

\[
\text{SAVING} = \text{SNAD} \cdot (a + b \cdot \text{SNAT}) - XMASVAC
\]  

\[\text{where: SNAT is seasonal normal actual temperature}
\]
\[= 3.7 \text{ deg C for week beginning 18 Dec}
\]

The regression parameters \(a\) and \(b\) are obtained by the
regression method outlined in Section 4.5 (see, e.g,
equations (4.1)), except that only term-time values are used
in the cross correlation (since we are estimating average
term-time demand levels). Besides, to include vacations in
the calculation of the slope parameter, \(b\), is invalidated
since there is no sensitivity to temperature outwith term
time. Not only is a vacation \(b\) not justified for this
reason, but there are too few vacation values for
statistical significance in any case.

In a similar way, the extra cost of one week's heat in
October is given by:

\[
\text{EXTRA} = \text{SNAD} \cdot (a + b \cdot \text{SNAT}) - \text{SUMVAC}
\]  

\[\text{where: SNAT = 10.0 deg C for week beginning 3 Oct.}
\]

We would expect this "EXTRA" to be somewhat less well
defined than the "SAVING", since the transition from
vacation to term in October is less obvious in the demand profiles, being late summer (Figures 4.1 and 4.2).

One would hope that the net gain, given by \((\text{SAVINGS-EXTRA})\), would be positive (for an overall saving). The results, for both KB and MB, are summarised below. They show that the net gain, when expressed as a \% of the total annual heating requirement (in those 2 years), reaches about 0.6\% and 0.8\% for KB and MB.

Table 4.7: The impact of rescheduling terms and vacations for energy conservation.

<table>
<thead>
<tr>
<th></th>
<th>KB (OIL)</th>
<th>MB (GAS)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(100 LITRES)</td>
<td></td>
</tr>
<tr>
<td>1.</td>
<td>SNAD (XMAS)</td>
<td>859</td>
</tr>
<tr>
<td>2.</td>
<td>XMASVAC</td>
<td>718</td>
</tr>
<tr>
<td>3.</td>
<td>SAVING (= 1-2)</td>
<td>141</td>
</tr>
<tr>
<td>4.</td>
<td>SNAD (SUMMER)</td>
<td>592</td>
</tr>
<tr>
<td>5.</td>
<td>SUMVAC</td>
<td>654</td>
</tr>
<tr>
<td>6.</td>
<td>EXTRA (= 4-5)</td>
<td>-62</td>
</tr>
<tr>
<td>7.</td>
<td>NET GAIN (= 3-6)</td>
<td>+203</td>
</tr>
<tr>
<td>8.</td>
<td>NET % GAIN</td>
<td>+0.59%</td>
</tr>
</tbody>
</table>

Compared to the 10\% target set by the Fuel Conservation Group, the savings are relatively small. Despite being modest, they do show that a real saving can be achieved, which is encouraging. The greatest motivation behind the exercise came from the use of meteorological data in making this assessment, to see how the saving compared to 10\%, and indeed to see if the sign was right (i.e. a positive saving). Quite apart from cost, other associated problems would accompany the suggested closedown (though not for the October week). These would include various administrative and staffing difficulties, and social reactions to such a move. The method also suffers from lack
of data and the fact that the term-vacation transition in October is relatively ill-defined. This is manifest in a negative extra cost for KB (Table 4.7), when one would not normally expect a saving at all in October. It should also be borne in mind that the figures relate only to 2 years data, and are no more general than all that implies. Financial savings are obviously possible, and the idea is intuitively appealing since it preserves the same total number of teaching weeks.

4.10.2. RE-ORGANISING OTHER BUILDING OCCUPANCY PATTERNS

Clearly, more data would provide a better estimate of the average saving, using long term means. Whether this would increase the potential savings remains an open question. The method has proved to be of interest from an energy conservation point of view, for it supplies an order of magnitude of potential saving. It should be noted that this is the only part of the thesis that will be involved with classical energy conservation as such.

The approach in general has a variety of interesting and useful implications for energy conservation management in a broader sense. These are applicable over a range of scales and involve the same fundamental principles and calculations used here. For example, it could be used to investigate fuel conservation resulting from all-night or weekend use of buildings, evening classes, etc, and building occupancy patterns in general.

The method could be adapted to cope with assessing financial savings from re-organising terms, school holidays, half term breaks, etc, in schools and colleges. There are also implications with respect to changing staffing patterns in commerce and industry, with a view to economising on total energy consumption. The approach also has repercussions at the national level in, for instance, estimating the energy savings resulting from the BST-GMT clock changes, and their time of year dependence.
4.11. CONCLUDING REMARKS AND SOME PROBLEMS

It is fairly well known now that energy demands undergo quasi-cyclic fluctuations on several distinct (though interacting) time scales. On a seasonal scale, focused on here, these variations are driven in part by the seasons but also by the composition of the University year. This study has shown that there is a close relationship between energy usage and weather at the local level, that of Edinburgh University. It has also thrown some light on some of the problems involved in analysing such dependencies. Certain aspects of the approach suggest possible applications of meteorological data in energy demand modelling. These points will now be expanded upon.

The apparent relation between fuel usage and atmospheric conditions is closely controlled by the selection of scale. Here, the space scale is two individual groups of buildings using gas and oil for several non weather-sensitive sectors besides heating. These will introduce inaccuracies into weather-demand models. It is an ideal space scale, on the other hand, to investigate local, micro-scale responses.

In addition to the relatively massive seasonal effect, we have discovered the existence of short-term (interweekly) sensitivity to temperature. We are obviously getting closer to the real short term response, since we are now dealing with actual consumption and not deliveries. In addition, a dependence on sunshine, and to lesser extent windspeed, was also brought out, even on this still quite coarse time scale. This is encouraging for the following studies.

The temporal scale has prevented the extraction of very short term (<1 week) reactions, such as daily responses. Such finer scale events are filtered out by weekly means. The temperature and wind data would perhaps be more useful as daytime values only. This would relate more realistically to building occupancy patterns. The continuous wind run included lower overnight wind values, which probably hides any daytime sensitivity.

The difficulties introduced by the special nature of
the data were introduced in Section 4.3. The problem is that since we are now at the microscale, i.e. individual buildings, there is too much centralised load management taking place and this sometimes disguises any weather dependence. Personal reactions to weather are not individually dictated, and as such the response behaviour is peculiar to these groups of buildings. As a result, the load-mix is also somewhat special. The results are still of general usefulness from the viewpoint of scale translation/hierarchies, as already examined.

Other factors also contaminate the data, such as Summer and Christmas vacation. These have a polluting effect on short term response. Though these were retained for some parts of the analysis, they were removed for others. The length of the series also imposed restrictions in places. The results are only valid for the 2 years looked at here. Clearly, more data is needed to clarify the results, and to continue the work generally.

The most important application of energy demand modelling on any scale is demand forecasting. Such usefulness is clear with finer time scale data where short term responses are not lost. This is impractical with weekly data, and we do not have accurate weather forecasts out to beyond 1 week ahead anyway. Weekly analyses could perhaps be potentially useful for general forecasting of heating plant size, base load, plant regulation, boiler house management, etc. Demand prediction could possibly be carried out using seasonal normal demand and temperature, but again several more years data would be needed. Even if demand forecasting applications are few, the work finally showed how useful weather data were in assessing the feasibility of rescheduling University terms with a view to saving fuel, and its variety of broader implications for changing building occupancy patterns in general.

Despite the limitations of weekly data, it appears from the evidence presented that the energy management system now responds more rapidly to temperature than in 1976/77 (both seasonally and short term). Further improvement is at present hindered by close involvement with
an energy conservation programme and the limited use of only weekend weather forecasts. It is hoped that eventually the microprocessor energy control system will connect all buildings on the campus. The use of meteorological information on a daily basis would surely improve demand estimates and hence the computerised co-ordination of supply by plant regulation, and consumer comfort.

So, we have modelled statistically, and interpreted physically, the effect of weather on energy usage on a local scale, for two individual groups of buildings. We have gained some insight into micro-scale reactions to temperature, solar radiation and windspeed on this time scale. As such, the approach has other microscale applications, such as fuel usage in schools, colleges, low energy housing schemes or residential estates, office blocks or larger groups of buildings. We have also discovered how the strength of correlation has improved over the previous monthly study.

It is obviously impossible to model thousands of separate microscale responses (e.g. individual homes or offices). This would involve fine monitoring of microclimate, etc, but we do know that these make up the regional total, which follows presently.

This scale translation is a very rewarding concept temporally, as well as spatially. It implies that many daily responses are averaged out with weekly data. Daily data at the regional level would seem to be the next suitable compromise on the spatial/temporal hierarchy (Chapter 1) for understanding more fully our reaction to weather. Using such knowledge, we can predict tomorrow's demand if we have tomorrow's weather forecast. We now show how this understanding and prediction is achieved to a high degree of accuracy at the daily regional level.
5.1. OVERVIEW

We now move on to the climax or core of the work, the problem of understanding and trying to predict the use of energy at the regional level of aggregation on a daily time scale. This Chapter and the next represent the author's work at its most useful and original, and has important real-time forecasting applications. In the previous case studies, we witnessed how difficult demand prediction was with coarse time scale data. This time, with daily regional data, we can achieve this successfully, and to a high degree of accuracy, having modelled the processes correctly.

This Chapter presents the formulation of a totally operational statistical model for forecasting daily energy demand, step by step. The model development is described in detail; Chapter 6 then applies this in practice to four in-depth Scottish and South-East English regional case studies of daily electricity and gas. A reference list of variables was provided at the start of the thesis; this may usefully be referred back to throughout both Chapters. Since we will be working with daily data, the reader will also find it interesting and helpful to recall the general comments made on daily electricity demand in Chapter 2.

In this Chapter, an introduction to meteorological aspects of the present energy management systems is first given, see also coverage of general aspects in Chapter 1. This is followed by a discussion of the data bank, with a consideration of sources of error and uncertainty, persistence and multicollinearity. The philosophy of the approach is explained and tests of model performance and forecast skill described.

The model itself is then derived. The raw meteorological variables are first converted into several "working" or "processed" parameters. These are "Effective
Temperature" (an exponentially weighted lagged temperature variable), "Cooling power of the wind (Windchill)" which is a non-linear variable controlling ventilation and air changes in buildings; and a further supplementary and unique index combining sunshine, rainfall and visibility empirically into a linear dimensionless quantity. This is the SRV statistic (Misery index), which is designed to incorporate psychological and social effects such as perceived dullness, raininess and daylight illumination (for lighting demand). A novel way of choosing an appropriate windchill statistic is presented. The weekly cycles are then removed and the stepwise interpolation technique introduced in Chapter 3 is used to remove seasonality and local trend. An autoprojection scheme for demand prediction is then detailed. The final demand forecasts are encouragingly accurate. The four parallel case studies of a 90-day winter period then follow in Chapter 6.

Hereafter, by "short term" we shall mean day-to-day (intra-weekly) variation. This inter-daily variation is quite distinct from "seasonality" and "local trend", discussed later, which collectively constitute inter-weekly variation ("inter" is "between", "intra" is "within").

5.2. CUSTOMER CLASS BREAKDOWN OF ENERGY USAGE (LOAD-MIX)

It is of special interest to the meteorologist to be aware of the multitude of end-uses of energy. In particular, he/she should be aware of the extent to which these are weather sensitive. Chapter 1 provided a brief overview of this customer class breakdown. A more complete treatment is given in Appendix 1 (in both diagrammatic and tabular form). The reader will find it instructive to refer to this from time to time, but should note that these are annual means. Load-mix and sensitivity do vary seasonally and daily. Only a summary is given here, and the figures quoted refer to 1979 unless otherwise stated. See also DUKES (1982).

The demand for (sales of) electricity and gas consists of a mixture (load mix) of industrial, commercial and domestic loads. These include energy for space- and water heating, air conditioning, and lighting (for electricity),
amongst others to be considered later. Heating is closely controlled by temperature, naturally enough, as we have already seen, but also by wind. Air conditioning and ventilation are also controlled by temperature and windspeed. Lighting is controlled by daylight illumination, and the total lighting load accounts for 17% of all electricity units sold. Lighting and wind-induced heating we have not yet tried to model, but they will be conclusively demonstrated to be of fundamental importance.

The industrial sector comprises the large scale manufacturing industries such as iron and steel, chemicals, paper and engineering, amongst others. This sector is mostly non-weather-sensitive (e.g. process heat, motive power, factory lighting).

Commercial premises include shops, offices, banks, hotels, schools, hospitals, public houses and other places of entertainment. Street lighting (highway lamps and road signs) also comes under the heading of commercial electricity, which takes up 12% of all electricity sold. Public lighting (e.g. shared staircases in blocks of flats) and traction (railways) are also important constituents of commercial electricity. Street and public lighting are not sensitive to the weather on a short term, daily basis (except photoelectric street lights), though astronomical forcing of daylength by the seasons means there is a pronounced annual cycle in their load curve. District heating schemes are as yet too underdeveloped to permit assessment of their weather dependence, but see BRE (1975) and Courtney (1976). Office, shop and school lighting (all mostly flourescent) are the most weather sensitive of the commercial sector, together with air conditioning.

The domestic sector embraces homes, flats, farms, and other private residential dwellings. This sector uses energy for cooking, lighting, refrigeration, space- and water heating. Duncan (1977) quotes that a typical family house uses about 50 KWh/day in winter, 30 KWh/day in summer; 10 KWh/day is for electricity, the rest being for space- and water-heating.

Since a large proportion of the total domestic load is
for space heating (69% and 27% for gas and electricity), this sector is particularly sensitive to the weather. 34% of all gas sold by BGC is destined for domestic space heating (10% of all electricity). The heating load consists of central heating, individual space heaters (e.g. gas fires, convective and bar fires), storage and fan heaters and underfloor heating. Gas has a 64% fuel share of the central heating market, whereas electric central heating takes a 22% slice. Gas supplies 50% of all heat used in homes and flats (electricity 19%). One would perhaps expect, in the light of these statistics (see also Appendix 1), that gas sales are more weather susceptible than electricity. We must await the case studies to see.

In a sense, the cooking component also has a weather dependence (e.g. compare salads on sunny summer days with hot meals in winter). The influence of atmospheric conditions on water heating and refrigeration is rather more difficult to ascertain. Domestic lighting is clearly governed in part by exterior illumination. The numerous domestic household appliances possess varying degrees of weather susceptibility. Such appliances include washing machines, irons, telephones, kitchen equipment, record players, freezers, TV and kettles. BRE (1975) estimate that such miscellaneous loads account for only 20% of domestic electricity. Though small, one would expect, for example, TV viewing and kettles to have some response to weather.

5.3. THE PRESENT ENERGY MANAGEMENT SYSTEMS

Every afternoon in the CEGB’s 7 Grid Control Centres and in British Gas Corporation’s 12 Regional Centres, a prediction has to be made of the following day’s demand (total unit sales). By demand is meant the expected take of electricity or Natural Gas from the National Grid and National Transmission System respectively. The North Sea gas supply companies are then informed of this demand, so as to send it via the onshore terminals of the producing companies. Similarly, the power stations are so informed. The gas moves relatively slowly, and it can take more than 3 hours to put an additional electrical generator on load.
Accurate demand predictions are therefore required, especially in severe weather. These forecasts, which principally cover up to 3 days ahead, are necessary so that low pressure gas holders, compressor stations, liquified natural gas (LNG) and power stations can be operated efficiently.

Regarding power stations, it is possible to arrange that just enough generating plant is being used at any one time, utilising the most economical plant. This is a cost optimisation problem and is an important day to day linear programming task in Operational Research departments within the fuel industries. The optimisation is achieved by the national coordination of power transfer on the Grid, by virtue of the system’s complete inter connectivity and centralised control. In essence, it is possible to load the CEGB’s power stations in such a way that the overall cost of generating on a national basis is at a minimum (Baker, 1977). The spinning reserve capacity (reserve plant needed to cover emergencies) is also minimised. Accurate weather forecasts are essential to the smooth day to day operation of this system of regional allocation and inter regional transfers. They are absolutely vital to plant regulation in winter. This enables the matching of supply and demand, and avoids under or overproduction of power.

Most of the generating plant is thermal, i.e. conventional coal or oil fired power stations. Thermal power stations provided about 85.0% of all electricity supplied in 1981. Nuclear power stations provided 12.8%, all of this being for (weather insensitive) base load. Hydro-electric stations (free running and pumped storage) supplied 2.1%. The Plowden Report (1976) describes the structure of the electricity supply industry in England and Wales.

5.3.1 CURRENT USE OF WEATHER FORECASTS

At present, the Area Electricity and Gas Boards have contracts with the Meteorological Office for the provision of special, regional, short term weather forecasts. These are prepared and issued 6 times daily for gas (i.e. updated every 4 hrs), and 5 times daily during the working day for
electricity (updated every 3 hrs). They emanate from Abbotsinch Weather Centre at Glasgow Airport for Scotland, and London Weather Centre for the South East (the two regions in the later case studies).

For gas, the temperature forecasts are for 2-hourly intervals, 4-hourly blocks for windspeed. Both are for the next 24 hrs, and are collectively known as METOGAS forecasts. For electricity the day is split up into 3-hour forecasting periods for both temperature and windspeed. Hourly demand prediction concentrates on the times of maximum demand, such as mealtime peaks, see hourly loci in Chapter 1. Provisional demand forecasts are revised in the light of further actual demand and weather experience (Barnett, 1972). Morris (1982) states that although Area Boards attach great importance to temperature predictions, they also give a significant weight to persistence. This is partly because sales lag behind changes in weather. Orders for gas or electricity, therefore, always use yesterday’s and today’s temperature, as well as tomorrow’s (Morris, 1982).

Besides temperature and wind (speed and direction), general information on cloud, precipitation, visibility and sunshine is also included. This is (for electricity) to make an estimate of daylight illumination for lighting demand, since no routine forecasts of daylight are supplied. For gas, a much more subjective view is taken of these factors. Within the electricity supply industry, an empirical measure of daylight (EI index) has been developed, to condense these variables into illumination equivalents (kilolux). This index was described in Chapter 1 and is totally different from the one to be developed here. The flux of daylight has been continuously recorded at Kew since 1947, and since then CEGB have installed several other illumination recorders, mostly for retrospective normalisation of sales (lighting component thereof).

The Gas Controllers and Electricity Supply Engineers are normally grateful for any other advice or additional information; e.g. London or Glasgow may not be always representative. In times of doubt, advice is sent out.

Also disseminated are twice daily forecasts of maximum
and minimum temperatures (TMAX, TMIN) for the following 3 days. All issues also contain actual readings since the last forecast. All this information is sent via the GPO telex directly to the computer system, where the telexes are decoded and stored in a weather data bank ready for demand prediction (Piggott, 1980).

The most important weather forecast is the 1600 hr issue (1530 hr for gas), which covers the following 24 hours (36 for gas). This particular forecast is used to assess the following day's demand, for it contains a regional average temperature and windspeed for the whole day. The Regions then have to place their orders with CEGB and British Gas Corporation (BGC) HG in London by 1630 hr. British Gas subsequently order their gas from the offshore companies before 1800 hr that day. Regional estimates are collated at National Control (for electricity) and BGC for a Global demand estimate. BGC and CEGB maintain that individual regional demand predictions are preferable to a global demand estimate, since the Regions are nearer to the local characteristics of their customers' response.

National Control and British Gas HG also receive hourly synoptic reports and plotted charts via the Landline Facsimile Ring Circuit emanating from Met.Office HG at Bracknell. These are especially useful in deducing the likely arrival of adverse weather conditions at large conurbations (Barnett, 1972).

5.3.2 DEMAND PREDICTION MODELS IN USE TODAY

For electricity, the weather sensitive component of demand is predicted by means of a multiple regression method due to Davis (1958) using these forecasts. A windchill parameter (temperature and wind combined, discussed later) and the EI index, are added after temperature (actual and lagged) in a dynamic multivariate scheme. For gas, short term forecasting procedures vary widely between regions. These include linear demand-temperature methods, Box-Jenkins, multiple regression using temperature and windspeed, manual methods, and analogue techniques (selection of a similar day profile). Some Gas Regions
wind—correct their temperatures before demand extrapolation. Other capricious wind correction factors and various cut—offs have been experimented with.

The weather sensitive load is then added to the underlying seasonal base load, which is usually a polynomial function of time of year and/or a function of earlier demand (autoregressive). A load growth term is also added in for long term trend. Many Regional Grid Control room staff remain convinced that simple demand—temperature regressions are the most reliable projection method (BQC, indirect communication). They have remained in use mainly for historical reasons (innovation vs tradition).

Since the advent of computer technology, this prediction phase is mostly computerised (though some Boards still retain manual methods). The model coefficients are continuously updated as new data becomes available (oldest data “falling off the bottom”). Hourly and daily demand extrapolation is linked on line to the telemetry system, and so processes all new weather data automatically, a so—called “rolling rate” forecast. Being dynamic, this forecasting method eliminates trend and seasonal effects, for it allows the coefficients to “drift” with short term changes in sensitivity. Output is displayed on a cathode ray tube (video) in both tabular format and as a continuously updating graphical display of actual and forecast demands. The Boards that do use, for example Box—Jenkins models, use this output alongside manual or regression methods. Even the peripherals to this linear dynamic model, such as statistical quality control, are normally quite sophisticated, being microcomputer driven.

The computer forecast is normally amended in the light of the operators knowledge and experience. This happens quite often, and is especially true with gas where a rather subjective view is taken of the impact of cloud, rain, and sun. Some Gas Boards have the attitude (private communication) that it is not worth the extra expense of collecting and analysing any additional meteorological data such as these. Even CEGB do not receive quantitative estimates of these, and prediction using them is performed
on a subjective basis. It is felt here that the present generation of models suffers on extreme occasions because of this subjective element. The most progressive or fashionable of such models are the innovative Box-Jenkins suite described in Chapter 2. BGC and CEGB are recommending their Boards at least to experiment with them, though there is a large amount of resistance and tradition to retain simpler schemes. These are at the opposite end of the spectrum of model sophistication (Chapter 1).

After running the prediction model using the weather forecasts, the nationwide co-ordination of generating plant and pipeline gas transmission are arranged. This linear programming phase has been mastered to a fine degree of accuracy. Mean operational forecasting errors are rarely published, with some notable exceptions. Baker (1977) quotes typical forecasting errors (rms) of 1.7% and 2.5% for CEGB 3-hourly and daily load predictions respectively. Thompson (1976) reports mean forecast errors of 3.5% for hourly load predictions on the Pacific Gas and Electric Co, San Francisco. He claims a reduction to 2.1% with his model. Barnett (1972) quotes standard deviations of 1.5% to 2.0% for CEGB 3-hourly forecasts using the method of Davis (1958). He continues by stating that these are approximately equally divided between model errors and weather forecast errors. He also feels, amongst others (personal communication), that further improvements are not worthwhile and possibly not achievable.

5.3.3 THE PROBLEM

Despite the highly advanced and organised energy management systems there are problems. In the severely cold weather of early 1979 and to a lesser extent in winter 1981/82, their models failed to cope with excessive demand. There was reduced gas pressure, voltage reductions, load shedding and emergency disconnections (power cuts). This arose because of insufficient generating plant due to sudden or protracted system overloading.

These underestimates have aroused some concern within both industries as to the validity of prediction models in
extreme events (see, for example, Energy Management, Feb 1982). Though the economics of the industries have changed rapidly, this is as much a problem now as it was back in the days of "Town Gas", when production plant was under serious strain in severe weather, causing rationing and schedules of reduced pressure. The problem of severe weather is even more acute in the U.S, e.g. Oliver (1973) emphasises that blackouts caused by extreme weather are becoming the rule rather than the exception in the States. In this country, CEGB try to insure against such emergencies (so called "wild forecast days") by running a "spinning reserve capacity", or by "pumped storage" schemes. In hydro-electric pumped storage schemes, electricity generated during off-peak periods is used to pump water to high-level reservoirs, from which it descends to drive turbines at peak periods or in severe weather.

At normal temperatures, because of the increasing sophistication of thermostatic and time controls (programmable clocks/ time switches), their automatic nature allows them to be set and left alone. Consumer response then becomes more predictable over certain temperature ranges. Clark (1979), however, reminds us of some of our wasteful and inefficient habits during extreme weather: clock controls are altered or overridden; thermostat settings are increased; secondary or back-up heating devices are lit to support undersized central heating installations; even the oven door is opened to heat the kitchen; and finally people switch fuels or maybe have no fuel at all if there are model failures resulting in supply cuts or reductions. These practices show that we are prepared to sacrifice economy and convenience to maintain higher standards of comfort.

It is strongly maintained here that there should be some re-examination of the use of meteorological data, especially in extreme and sudden events. SSEB and the Electricity Council, as well as Scottish and N. Thames Gas support this need (personal communication). Only occasional Working Parties have attempted it, and the results are confined to Internal reports and papers. It is really only since the severe winter of 1979 that the problem has been
investigated, since the massive forecast errors in that winter.

The problem is not only to investigate these severe events, but to understand generally, and hence build models for, consumer reaction to the weather so as to predict future demand. The heart of this work will be concerned with this problem of modelling and then forecasting demand, not just extremes but also in general. One can then, as a corollary, go on to look at extreme events. The next Section explains how we will tackle this central problem of modelling and forecasting daily energy consumption.

5.4. PHILOSOPHY AND PURPOSE

This Chapter and the next have four main goals: a) to develop several statistical parameterisations of the weather, some unique, some semi-standard; b) to mathematically model the dependence of daily electricity and gas demand on these composite variables. Having understood the scale and nature of this response, we can then c) objectively derive and critically assess an operational statistical model for predicting demand using weather forecasts; and d) examine more closely the influence of synoptic situation (especially extreme and sudden events) on demand through detailed case studies. Here again, the approach will be unique, for it carries out comparisons between synoptic situation and residual errors.

Though the approach is primarily statistical, high emphasis will be placed on physical meaning. In addition, a critical evaluation of the model construction will be undertaken. The contribution will then be related to the broader aims of demand modelling and various more general philosophical issues.

To elaborate a little, the modelling and forecasting task naturally falls into three parts. Firstly, to model demand–weather relations is necessary, so as to understand the fundamental principles governing reaction to weather. Secondly, predictions of demand can be made. To this end,
the data sets will be split into halves, model coefficients derived from the first half will be used to predict the second half. Thus we are testing the model on independent data, though the model is still one step removed from reality. This is because we are still assuming weather forecasts to be perfect. Thirdly, therefore, to be more realistic, we will artificially simulate (randomly) weather forecast errors (temperature and windspeed), for the second half. When running in this mode, the model is totally operational and unbiased and can be used for real time applications. It assumes nothing about the future at all and is totally realistic in every way.

As explained in Chapter 2, the approach rests on the assumption that the demand time series can be decomposed into several distinct non-interacting components on various time scales. Raw demand comprises the annual cycle (seasonality or local trend), and the weekly cycles, which together can be thought of as a kind of base load. Superimposed on these is the irregular, apparently stochastic, weather-susceptible component. The seasonality and weekly cycles represent the slowly varying, low frequency component which is to some extent deterministic and therefore predictable, but which varies almost imperceptibly from day to day. They may therefore be removed. The (seemingly) more erratic high frequency noisy part varies rapidly and noticeably and is hence inherently less predictable. It is attributable mostly to the atmosphere, but also to a host of other causes such as strikes, industrial action, bank holidays (movable and fixed), fuel price variations, etc. We will not be considering the effects of prices (step changes and inflation) and other economic factors; these are assumed to be lost in the noise. There are all sorts of tariffs for cheap lighting and heating in industry (time switches, storage heating, etc). These only become significant with hourly data. For daily data over 3 months, to suppose price effects are negligible turns out to be a palpable assumption.

The mathematical/statistical model developed here is a
combination of an additive and multiplicative formulation. This was arrived at to ensure the reproducibility of the original series. This also ensures the valid attachment of physical meaning to each component of the series.

Although domestic consumers are heavily influenced by temperature, this study conclusively demonstrates the need to incorporate other meteorological parameters. Several physical/statistical parameterisations of the weather are constructed for this purpose. In particular, it is the intention to investigate extreme synoptic events to probe the reasons for occasions of present model failure. Though demand predictions were in error on these occasions, it should be noted that there are two aspects of forecast accuracy relevant here. Current models failed either because a) they did not have extremes built into them or b) the model was correct and complete but weather forecasts were erroneous. As outlined above, the model to be developed here will run in two modes, i.e. assuming perfect and erroneous weather forecasts. Comparison of the two will allow an assessment of deficiencies in the modelling process, i.e. how adequately we have modelled the meteorology.

Similarly, it should also be made clear that we will be looking at the effect of weather on the system load from the point of view of weather-sensitive demand (heating, lighting, etc). This is distinct from the direct effects of the atmosphere (i.e. not via demand) such as power cuts arising from frozen pylons, lightning, riming, burst or frozen pipes, and gales. These interruptions/breakdowns are not regarded as model failure here, and will not be discussed; likewise with power cuts due to industrial action. The energy authorities do use forecasts of lightning or icing risk. Similarly, weather forecasts are also used for planning repair and maintenance schedules, but these aspects of using meteorological data will not be considered.

The real problem is that extreme atmospheric events, by their very nature, are not very well documented, since by definition they occur infrequently. As a result, there are insufficient data concerning them to integrate into prediction schemes. Attempts to deal with them range from
probability theory and return periods, to load duration curves. Such medium and long term energy planning strategies, such as predicting Average Cold Spell (ACS) demands, were covered in Chapter 1, as well as short term. Note that only short term (daily) demand forecasting will be attempted here. In the present study, using synoptic situation to complement the statistics will prove very useful in this respect. This is because this allows physical understanding of such events by the various weather parameters, whilst still maintaining statistical rigour.

5.5. THE ENERGY DATA BANK

The energy data bank consists of four distinct (though parallel in time) data bases. These are:

a) daily electricity demand for South Scotland Electricity Board: “SSEB”;

b) daily gas demand for Scottish Gas Region: “SCGAS”;

c) daily electricity demand for South East Electricity Board: “SEEB” (actually Grinstead Grid Control Area); and

d) daily gas sendout for North Thames Gas Board: “NTGAS”.

All these data sets are for the 3-month period from January 1 (Monday)- March 31 1979 (90 days). Hence we have a comprehensive data bank allowing regional comparisons between 2 Scottish and 2 English Regions. This is the advantage of having temporally parallel data streams. The Electricity and Gas Board Regions are shown in Figure 5.1. All these data streams were read off Magnetic Tapes supplied by the appropriate Authority/Board.

1979 was a year with a severe winter, and it was felt here that it would be interesting and useful in this context since:

1) demand predictions were underestimated on several occasions, as already detailed; hence

2) there is some concern within the power industries as to the validity of forecasting schemes in severe weather, and

3) the winter 3 months lie in the depths of the heating season, when demand is at its most sensitive.

Though the minima were not quite so extreme as winter 1981/82, the severely cold and persistently snowy weather
Figure 5.1: The Regional Electricity and Gas Area Boards

(After Department of Energy, 1982)
was far longer lived than that winter. Work has been done here on summer data sets, but the effects of temperature and wind on demand are far less marked outwith the heating season. The winter months are the major concern of the fuel industries, since chances of load underestimates are greatest then. The opposite situation of overproduction is rarely a problem, the 1976 drought/heat waves being a notable exception.

The daily electricity and gas raw consumption series are presented in Figures 5.2 and 5.3. The units of gas are Therms (1 Therm = 29.3 KWh) and those of electricity are MWh (1000 KWh). These units will be adhered to throughout. Before commenting in detail on these series it is necessary to explain how the values were obtained and the various corrections which had to be carried out. This enables an assessment of possible sources of error or uncertainty. Hereafter, the words demand, sendout (for gas) and consumption are assumed synonymous and are freely used interchangeably. On the regional scale, with the exception of severe weather and model failure occasions, the assumption of energy sent out being energy actually used is realistic.

Both the Scottish demand records were obtained by integrating the 24 hourly system demands for each day. Both English series were already daily system totals. The N. Thames gas data are for 0600-0600hr, since the "gas day" (for telemetry) begins at 0600hr. Scottish Gas daily demands were integrated hourly demands, and so these are 0000-0000hr. Both electricity series were also midnight to midnight.

Certain adjustments had to be made to these raw data to arrive at a value most representative of the population's (civilian, not statistical) demand for energy. For example, a correction had to be made to the daily gas totals for interruption. This is because some industrial and commercial consumers have contracts which allow their supply to be interrupted during periods of high demand (e.g. severe weather). Such interruption occurs during so-called Standby or high risk periods when their supply can be terminated at
Figure 5.2: The raw daily electricity and gas demand series for Scotland, 1 Jan – 31 Mar 1979.
Figure 5.3: The raw daily electricity and gas demand series for S.E. England, 1 Jan - 31 Mar 1979
any time. Adding this back in provides an estimate of demand that would have occurred in the absence of interruption.

This is a potential source of error, though the Boards feel (personal communication) that on a daily basis it is very unlikely to introduce significant errors. The introduction of interruptible contracts has now become widespread, mostly among large industrial and commercial customers. There are no commercial arrangements for interrupting electricity, though a small amount of load management does occur such as voltage reductions. Any restrictions that do occur therein are usually the result of exceptional circumstances such as industrial action, but these data sets are not so affected.

The electricity figures were obtained by subtracting net interchanges (between SSEB or SEEB with CEGB and surrounding Regions), from the total power sent out from the Board’s generating stations. This inter regional transfer has already been described as part of the regional allocation strategy for co-ordinating the match of supply and demand. These are then "requirements" on the Board. These requirements are not electricity actually used (i.e. demand or sales) but that which the Board is required to supply to the Grid. Requirements differ from electricity units (KWh) sold, because of transmission and distribution losses. Such losses between power station and customer represent about 11% of unit requirements (Electricity Council, personal communication). This constant % correction was therefore applied. Here is another possible source of error, for not only is it load dependent but it may not be a constant proportion. SSEB and Electricity Council have the view that with daily data it is perfectly safe to assume this is constant (though not for hourly). Such sources of error are tiny compared to variability in the weather.

Referring to Figures 5.2 and 5.3, the first point of interest to note about all series are the weekly cycles. These are rather more pronounced for electricity. Daily demand is consistently lower at weekends due to the virtual absence of industrial and some commercial loads. It normally reaches a peak about midweek, due to the build up of
industrial (including 24 hour, continuous) processes, and the subsequent run-down thereafter. This variation between weekdays and weekends is normally about 10% of the total load. These regular periodic oscillations are understood and predictable and can therefore be removed (a process that will here be termed "deweeking", the resulting data being "deweeked data").

The next thing of concern to us is the general decrease in levels of consumption with time, with several exceptions such as the mid-February blizzard (day 46). This overall decrease we shall refer to as "seasonality" and "local trend". It results from a subsection of the annual cycle due to the approaching Spring, and cold/warm spells on the time scale of weeks.

The Feb 15 peak (Day 46) is a very famous day within both the Electricity and Gas industries. It is notable historically since demand soared well above average, and large underestimates of demand occurred, due to model failures of the type described.

We can also notice some additional interesting features from Figures 5.2 and 5.3. Days with high demand tend to follow days with high demand, and vice versa, i.e. there is some persistence or inertia in consumption levels. This will be pursued Section 5.6.4. There is clearly, too, an erratic variability between days, due mostly to the weather. The bank holiday Jan 1 (and Jan 2 for Scotland) are clearly anomalous (Figures 5.2 and 5.3) and will have to be dealt with (i.e. adjusted accordingly).

5.6. THE METEOROLOGICAL DATA BANK

For Scotland, the raw (untransformed) meteorological data base comprises daily values of temperature (TA, in deg C), windspeed (U, in knots), rainfall duration (RD, in minutes), sunshine hours (SUN), and visibility (VIS, in km). With the exception of SUN all these variables were measured at Glasgow Airport (Abbotsinch). This site would be expected to be well representative of the spatial concentration of demand in Scotland's Midland Valley (Figure 5.1), and this was tested (see later). Daily sunshine hours were derived
from the average at 3 Scottish stations: Prestwick, Abbotsinch and Leuchars.

For S.E. England, the raw weather data consists of daily values of temperature and windspeed (same abbreviations and units as above) at Gatwick Airport, Surrey, and sunshine hours at Heathrow Airport. No visibility or rainfall data were available for England on the Met. Office Magnetic Tape. Both airport sites are clearly well representative of the areal distribution of demand density, most of the demand in the S.E. being concentrated in Greater London itself. The daily TA and U values are temporal averages; how these were obtained for both England and Scotland will now be detailed.

5.6.1. THE TEMPORAL WEIGHTING SCHEME

For the S.E., the daily means of TA and U at Gatwick were calculated from a non-weighted average of readings at the clock times 09, 12, 15, 17, 21hr. This would appear to adequately reflect higher demands during the working day. There are no overnight values, these were the only hours available from an Electricity Council magnetic tape. It was felt here that such a daily mean is an improvement on a simple average of Tmax and Tmin. A very large proportion of the total daily system load occurs within or close to these clock times (see hourly profiles in Figure 1.1). The gas day of 0600-0600hr for N. Thames data is no problem in this weighting scheme, for the above clock times fall well inside this gas day.

For the Scottish data, the temporal weighting scheme was somewhat more involved, since the weather (and demand) data were derived from a separate hourly data base.

The daily values of TA, U, VIS, and RD were obtained from hourly values acquired from a Meteorological Office magnetic tape via SSEB. The hourly TA and U values were temporally weighted according to the average hourly demand for that time of day. The resulting daily mean satisfactorily reflects the temporal concentration of demand in the middle of the day (the "living day"), and attaches appropriately smaller weights (though not zero) to overnight
values. The equation used to perform the weighting was (using TA here, but exactly similar for U):

\[
\overline{TA}(i) = \sum_{j} \text{Weight}(j) \times TA(j)
\]  \hspace{1cm} ---(5.1)

where: \(i\) is day number (1..90); \(j\) is hour (1..24)

\[
\text{Weight}(j) = \frac{H\text{mean}(j)}{D\text{mean}};
\]

\[
H\text{mean} = \text{average demand for that hour};
\]

\[
D\text{mean} = \text{average daily total demand}
\]

For TA, such a scheme is more realistic than ordinary means of TMAX and TMIN used by most Area Boards. For prediction, simpler means would have to be used, unless we were given an hourly profile of forecast temperatures (which is sometimes the case for bench demand prediction).

For visibility, all hourly values outwith daylight hours were excluded from the calculation. This is because visibility is clearly irrelevant in darkness situations. Since VIS turns out to have so small an effect (on its own), a straightforward non-weighted mean was taken for hourly values between sunrise and sunset.

Regarding rainfall, the total integrated duration (in minutes, unweighted) for the whole day was used. This is because rainfall will also exert an effect on fuel usage outwith daylight hours (e.g. evening) by forcing people to stay indoors.

For Scotland, an experimental spatial weighting scheme for TA and U was undertaken to test the representativeness of Glasgow. It involved areally averaging readings at Abbotsinch, Prestwick (West Coast), and Leuchars in Fife (representing Dundee and Edinburgh), as taken from the Daily Weather Report. The results were not encouraging as there was no improvement in forecast accuracy, and some cases actually exhibited a slight worsening. It is conceivable, though, that even if on average there is no improvement, on isolated occasions areal averaging schemes may be worthwhile. The method was abandoned in favour of the previous formulations. Glasgow may be taken as representative of the geographical distribution of load.
density. Hence, the initial formulation will be adhered to throughout the analysis. For S.E. England, London is unambiguously representative of the population's demand.

5.6.2. GENERAL PROPERTIES OF THE WEATHER DATA

All of the raw meteorological records, for both England and Scotland, are presented in Figures 5.4, 5.5, and 5.6. A few general comments are relevant here.

Both temperature series show a general upward trend as the Spring approaches, superimposed on which are cold and warm spells on the time scale of several days or weeks, and day to day variability. Note too the persistently low levels of TA for long periods which was characteristic of this winter. Comparison with Figures 5.2 and 5.3 reveals a broad temperature dependence of demand; note especially the mid February and mid January blizzards.

Windspeed too shows variability on the intra-weekly time scale, but is somewhat more erratic and exhibits little seasonality. Rainfall duration, visibility and sunshine show this same time scale of variation; this is a point to be pursued shortly in the consideration of persistence. Sunshine also possesses a gradual increase in mean, and in variability (heteroscedasticity) due to the incoming Spring.

There now follows a brief description of the main synoptic events of the period to place these plots in context. As we shall see, synoptic situation turns out to be extremely important.

5.6.3. SYNOPTIC CHARACTERISTICS OF THE PERIOD

The period January to March 1979 was a very interesting one synoptically and was the coldest in Scotland and England as a whole since 1962/63, in some parts since 1940. January and February were very cold and snowy with only brief milder spells due to vigorous warm sectors. Snowfall was heavy at times and the persistently frosty weather maintained the snow cover for long periods. Gale force winds, often easterly, caused severe drifting and resulted in much hardship and some loss of life. March started mild but became very cold with heavy snowfall in the
Figure 5.4: The raw daily temperature (TA) and windspeed (U) records for Glasgow Airport (Abbotsinch); 1 Jan - 31 Mar 1979.
Figure 5.5: The raw daily visibility (VIS), sunshine (SUN) and rainfall duration (RD) traces for Glasgow: 1 Jan – 31 Mar 1979.
Figure 5.6: The raw daily temperature (TA) and windspeed (U) records for Gatwick, and sunshine hours (SUN) for Heathrow; 1 Jan - 31 Mar 1979.
third week. The month as a whole was cold, wet and windy. Mean winter temperatures were well below normal everywhere with anomalies of -2 to -3 deg C (January -3 to -4 deg C). Repeated outbursts of bitterly cold northerlies and easterlies were responsible for the long, cold and snowy winter.

The year commenced with severe frost and complete snow cover over the whole of Scotland and England. This is remarkable in itself, but as an Atlantic depression moved SE, gales caused heavy drifting on 4th. There was a brief mild spell 6-7th, but a further cold wave bringing heavy snow returned on 10th.

A warm front moved N.E. on 14-15th, bringing milder weather with a Tropical Maritime flow, but a new cold spell began behind a cold front moving S. Winds then became northerly as high pressure built over Greenland and there were further falls of snow as fronts moved S.

The cold northerlies of late January persisted into February. A small mobile high crossed Scotland on 5th bringing some sunshine and the next few days were cold, dry and frosty. A short lived milder and more gentle interlude was then very quickly followed by a fresh outburst of Arctic Continental air with NE gales and frequent snow showers. There was severe drifting on 14-15th; this is the famous peak shown on Figures 5.2 and 5.3. Depths of level snow exceeded 30 cm in parts of E. Scotland and temperatures stayed below freezing for 5 days in many places. We then began to get into a somewhat more mobile progressive pattern after Atlantic fronts encroached into W areas, with more normal temperatures until 21st. We then entered a blocking regime which persisted for 1 week with frost and freezing fog.

The mobile westerly type became re-established in March, with Atlantic fronts moving quickly E across all areas, with mild, wet warm sectors. By 13th high pressure was established E of Greenland, and the country was covered with a showery northerly flow. The pattern was then blocked for several days and there were Easterly blizzards on 17th and after, in both England and Scotland.
5.6.4. MULTICOLLINEARITY, NORMALITY AND PERSISTENCE

There are a number of relationships between the meteorological parameters which we shall find very useful in subsequent analyses. These require physical explanation. This multicollinearity is very similar for both Scottish and English data sets (though there is no VIS or RD data for S.E. England). The partial cross correlation matrix for Scotland is reproduced in Table 5.1, with appropriate persistence statistics to be detailed soon.

Table 5.1: Multicollinearity analysis (partial cross correlation matrix) of raw meteorological variables for the Scottish data bank

<table>
<thead>
<tr>
<th></th>
<th>TA</th>
<th>U</th>
<th>RD</th>
<th>SUN</th>
<th>VIS</th>
<th>ENR</th>
<th>n</th>
<th>MEAN</th>
</tr>
</thead>
<tbody>
<tr>
<td>TA</td>
<td>1.00</td>
<td>0.53</td>
<td>0.30</td>
<td>-0.11</td>
<td>0.20</td>
<td>2</td>
<td>30</td>
<td>1.7 deg C</td>
</tr>
<tr>
<td>U</td>
<td>-----</td>
<td>1.00</td>
<td>0.19</td>
<td>-0.17</td>
<td>0.02</td>
<td>2</td>
<td>30</td>
<td>10 kts</td>
</tr>
<tr>
<td>RD</td>
<td>-----</td>
<td>-----</td>
<td>1.00</td>
<td>-0.35</td>
<td>-0.29</td>
<td>2</td>
<td>30</td>
<td>150 mins</td>
</tr>
<tr>
<td>SUN</td>
<td>-----</td>
<td>-----</td>
<td>-----</td>
<td>1.00</td>
<td>0.47</td>
<td>1</td>
<td>45</td>
<td>2.8 hrs</td>
</tr>
<tr>
<td>VIS</td>
<td>-----</td>
<td>-----</td>
<td>-----</td>
<td>-----</td>
<td>-----</td>
<td>-----</td>
<td>-----</td>
<td>17 kms</td>
</tr>
</tbody>
</table>

Those coefficients in excess of 0.21 are significant at 95%.

Firstly, TA and U possess significant (>99%) multicollinearity. This was considerably less for the S.E. where $r=0.30$ (95% significant). They are positively correlated since in this particular data set, strong winds tend to correspond with high temperatures, on average. This is plausible in synoptic terms since the lowest temperatures tend to occur under an anticyclonic regime with clear skies and little wind. In contrast, strong winds are usually associated with a more cyclonic progressive pattern, i.e. a changeable, more unsettled westerly type with cloud cover preventing low TA. In this data set, strong winds were often associated with a mild SW Tropical Maritime flow within vigorous warm sectors, though exceptions did occur (e.g. Easterly gales). These considerations serve to give us an initial indication or hint at the importance of synoptics.
Surprisingly, perhaps, there is no positive correlation between TA and SUN. This is probably because the few sunny days in this period occurred under clear but cold anticyclonic regimes, typical of winter time. In data sets of this size, it only needs several such days to bring down the TA vs SUN correlation.

All other significant relationships in the partial cross correlation matrix (Table 5.1) are seen, with a little thought, to comply with physical expectation; e.g., on average, higher rainfall goes hand in hand with low visibility. The only other relation particularly worthy of comment, and which is slightly more subtle, is TA vs RD \( (r=0.30) \). This positive correlation arises because in this period most of the rain which did occur came in on a mild SW flow (active warm sectors). Though frequent snow showers did occur in cold NE winds, the actual duration of precipitation therefrom was comparatively small.

Moving now to normality, Figure 5.7 collates all the relative frequency (probability) distributions of the raw Scottish meteorological variables, and includes SSEB demand too as an example. TA and demand are approximately symmetrically disposed about their means, and the normality test described in Chapter 2 confirms they are almost normal. In contrast, RD, VIS, U and SUN are positively skewed, due to the sharp cut off at zero.

As we observed from the raw plots, all the weather variables show variation on the time scale of several (intuitively about 2-3) days. To corroborate this persistence, the correlograms for the raw Scottish meteorological parameters are given in Figure 5.8, in which some Acf's are superimposed. Where this occurs, one Acf will be plotted with crosses and one without. Despite being contrary to our convention laid down in Chapter 2, this eases recognition when superimposed. TA, U, VIS and RD all show serial correlation effects, suggesting sunny days follow non sunny days almost randomly. This is meteorologically reasonable since there were very few sunny anticyclonic spells in this period, which would have tended
Figure 5.7: The % frequency (probability) distributions of the Scottish meteorological variables, and SSEB demand.
Figure 5.3: The autocorrelation functions of the Scottish daily meteorological data (visibility, windspeed, temperature, rainfall duration and sunshine).
to introduce some persistence into sunshine.

The autocorrelation of the weather variables confirms the existence of a certain inertia in the weather pattern i.e. cold and warm spells, windy and calm periods and wet/dry spells. This variability on the time scale of several days we have already noted from the raw series. It demonstrates that the large scale circulation pattern, and hence synoptic scale motions, have a built in tendency to persist or evolve in one way in preference to another (Chandler and Gregory, 1976), once established. This inertia or “mood” of the atmosphere corresponds with what we know about blocking versus progressive patterns and persistent synoptic regimes in general. It is consistent with the life span of travelling synoptic scale disturbances in the mid-latitude westerlies. All in all, it is a fascinating aspect of atmospheric behaviour on this time and space scale.

This consideration of the statistical (persistence, multicollinearity and normality) characteristics of daily meteorological data is believed to form an important framework for the work as a whole. There is a notable shortage of attention to such characteristics from these viewpoints in the body of literature, see Panofsky and Brier (1958), Brooks and Carruthers (1953) for general comments.

5.7. DESIRABLE PROPERTIES OF DEMAND FORECASTING MODELS

We now list some properties that we would hope our demand forecasting model will possess.

1) The model should use as much relevant meteorological data as necessary; how many variables to use was discussed in Chapter 2 as an optimisation/linear programming problem in Operational Research (law of diminishing returns, etc).

2) The weather stations used should be representative of the regional variation of demand.

3) The model should be free from serious multicollinearity. Care will need to be exercised here due to TA vs U (but not for the S.E.), though all other relations are unaffected.

4) The model should be free from serial correlation/persistence effects. This is why it will be necessary to deweek and deseasonalise the data. Inclusion of seasonal and
cyclical effects would induce harmful spuriousness in this respect. This would also hide the inter-daily weather dependence.

5) The residual and forecast errors should obviously be minimised. Additionally, they should also be normally distributed and almost stationary white noise. Both these assumptions will be tested.

6) Errors in meteorological forecasts should also be minimised.

7) The model formulation should have a firm physical foundation, and the statistical techniques should realistically represent this physical/meteorological basis. This will considerably aid the interpretation of consumer behaviour.

5.8. ASSESSING MODEL PERFORMANCE AND FORECAST VERIFICATION

5.8.1. DIRECT MEASURES OF ACCURACY (SKILL STATISTICS)

It is very important in energy forecasting applications to establish the accuracy of the models used. At the end of each model run, therefore, an objective evaluation will be made of model performance and accuracy, in order to validate (or otherwise) the formulation. In addition to the final demand forecast, this will also be carried out after adding each variable stepwise. This enables the assessment of each variable's usefulness in reducing forecast errors. This verification procedure was achieved in a variety of ways, using a number of different skill statistics/measures of success.

Perhaps the simplest measure of forecast accuracy is the difference between actual (RAW) and forecast (FC) demand. Forecast Errors (FE) were therefore computed, where

\[ FE = \text{Actual} - \text{Predicted Demand} \]

These are directly analogous to "residual error", except that we are now looking at true forecasts and not simply attempts to postdict demands that have already occurred. Residual errors are a very useful measure of how well the model postdicts (backcasts) past data. Forecast errors, on the other hand, reflect the true forecasting power of the model when applied independently to
(i.e. tested on) the second half.

Mean absolute (modulus) and actual Forecast Errors, \(|FE|\) and \(FE\), could then be computed to represent the overall aggregate model performance. The Percent Error (PC) could also be found by expressing \(FE\) as a % of raw demand:

\[
PC = \frac{\text{Actual} - \text{Predicted}}{\text{Actual}} \times 100\% \quad \text{(5.2)}
\]

Similarly, mean modulus % errors (\(|PC|\)) were computed; this particular skill statistic has the important advantage of comparability between totally different data sets.

One would hope that the mean actual forecast error is close to zero. If \(FE\) is significantly different from zero, this would indicate a systematic bias in the forecasts which would need to be counteracted, if the cause was known. Hence it becomes very desirable to test whether \(FE=0\), and the following Section explains how this is done.

It is important that the forecast errors are near normally distributed and that they possess insignificant autocorrelation. These will be tested by % frequency (probability) distributions and correlograms respectively, though the results will not always be presented.

An additional useful measure of success, which we will always quote, is the cross correlation coefficient between the actual and predicted values. The significance of the difference between the means \(\overline{RAW}\) and \(\overline{FC}\) will also be tested. This is equivalent to asking if the two sample means (\(RAW\) and \(FC\)) are drawn from the same population. This too will be described shortly.

To substantiate these methods of forecast evaluation, the root mean square forecast error (rms \(FE\)) was also computed, where:

\[
rms \ FE = \sqrt{\sum (\text{Actual} - \text{Predicted})^2} / N \quad \text{(5.3)}
\]

This is analogous to the standard error of estimate (see Chapter 2, equation (2.8) where it was applied to residual errors); here it is applied to true forecast errors. The rms PC will also be calculated from this.
If \( \overline{FE} \) (not \( |FE| \)) = 0, then equation (5.3) becomes the standard deviation of the forecast errors, which will be extremely useful to know in all practical applications of forecasting. This is because knowing this, one would have a known margin of error when making predictions. More precisely, if the FE are near normally distributed, then we can be 95% certain that our FE will lie within 2*rms FE of the mean FE(=0), and 68% sure it will fall within 1 rms FE of zero. Provided the assumption of normality is met, then this is a very valuable result in energy modelling and forecasting for real-time applications.

5.8.2. STATISTICAL TESTS OF SKILL

Is the mean actual forecast error significantly different from zero? Equivalently, is there a systematic bias in our demand predictions? To test whether \( \overline{FE} = 0 \), the Zo test was employed (analogous to Student's t test but for large (>30) samples). We define the test statistic, Zo, by:

\[
Zo = \frac{\overline{FE} - 0}{\sigma_{FE}}/\sqrt{N} \tag{5.4}
\]

where: \( \sigma_{FE} \) = standard deviation of forecast errors

We are effectively testing whether our sample mean (FE) equals the population mean (the hypothesised value of 0 in equation (5.4)). This Zo statistic is normally distributed, hence its significance may be tested using probability tables of areas under the standard normal (Gaussian) curve ("z tables"). For further general guidance on hypothesis testing and z tests, see Spiegel (1972). The results of the test will always be presented with each model run.

Are \( \overline{FC} \) and \( \overline{RAW} \) different enough to indicate that they have been drawn from different populations? That is, are these means significantly different? Once again we need a z test (t test for small samples), this time a version of it applicable to testing the difference of two means. The appropriate test statistic is defined by:
Probability tables are then used, as before, $z$ being normally distributed.

### 5.9. Establishing the Processed Meteorological Parameters

Returning to meteorology, this Section describes how the raw weather data are transformed into several "working" or "processed" composite model variables. The development of each index is described in detail. The raw data are converted to a form which is not only computer compatible (suitable for statistical analysis operationally) but which more realistically relates to demand in physical terms.

#### 5.9.1. Effective Temperature (TE)

**5.9.1.1. Non-linearity Considerations**

Temperature is the most important single meteorological variable affecting energy demand. It is also the most easily understood. The Domestic sector in particular is very sensitive to temperature changes, since this part of the market includes space heating and central heating, amongst others already listed.

So far in this study the response to temperature has been assumed, and proven, to be linear. Rose (1949), however, gave evidence from the Gas Light and Coke Co in 1938, of increasing sensitivity of gas demand at lower temperatures. Clark (1979) suggests this non-linearity could exist because as temperatures become more extreme, then diversity of customer behaviour lessens rapidly. His example of non-linear sensitivity (decreasing sensitivity above a threshold comfort temperature, $T_{COMF}$) was reproduced in Chapter 1. The non-linear curve obtained by Warren and Leduc (1981) was also given, and showed increasing sensitivity above $T_{COMF}$ due to air conditioning/ space cooling.

Some Boards use forecasting schemes that involve power curves or parabolic functions (mostly quadratic or cubic), though Clark (1979) confirms that only 2 of the 12 Gas
Regions then used curved temperature-demand models. The Gas Council in 1979 suggested a straight line approach; such recommendations are contained in the Working Party Report EPC 86 (Corporate Planning, N. Thames Gas). This is still very much the consensus of opinion today. Baker (1977) states the use of a parabolic temperature parameter \(a \cdot TA + b \cdot TA^2\) for CEOB load prediction. The authorities using non-linear methods normally use a graphical curvilinear multiple regression analysis, (see Ezekiel (1941)), which is empirically, not physically, based. The evidence presented and to be presented forces us to pursue linearity here.

5.9.1.2. SELECTING A WEIGHTING SCHEME FOR EXPONENTIAL SMOOTHING

In addition, it has already become clear in this study, from various considerations, that domestic consumers have a certain lag in their response to TA. Firstly, part of the persistence in demand is probably being forced by the persistence in TA. Secondly, the lag-cross-correlation of demand with previous day’s TA was almost as high as with today’s TA. Since the lag in TA (about 2-3 days) is considerably less than that in demand (shown later), there must be some delay in consumer response. This strongly hints at the need to derive a temperature statistic that takes into account previous day’s TA. The persistence in temperature in itself supports the need to formulate a model that takes explicit account of such serial correlation effects. Some Boards get over this problem by including an autoregressive term in their demand forecast.

Though recognised implicitly, several studies have omitted to incorporate this daily lag effect into their formulation. This is particularly true of earlier literature, e.g. Dryar (1944) and Rose (1949). A simple refinement would be to try to build in this effect by defining TA to be the mean of today’s and yesterday’s TA. Furthermore, it was hypothesised here on similar grounds that demand is influenced not only by yesterday’s TA but to an ever-decreasing extent by the temperature of previous days. That is to say, there is a high degree of inertia or lag in the system.
To test this hypothesis a definition of "Effective Temperature" (TE) was established here, where TE is given by

\[ TE(i) = m \cdot TA(i) + (1-m) \cdot TE(i-1) \]  

--- (5.6)

where: \( TA(i) \) is today's actual, \( TE(i-1) \) is yesterday's effective; \( 0 < m \leq 1 \), and i is day number.

This definition of TE is to some extent arbitrary, being some weighted combination of \( TA(i) \) and \( TE(i-1) \). Clearly, when \( m=1 \), TE in equation (5.6) reduces to just TA. To decide on an optimal weighting scheme, i.e. a value for \( m \), all values of \( m \) between 0 and 1, in steps of 0.1, were tried. The one yielding the strongest cross correlation with demand was chosen. The value of \( m=0.5 \) was found to consistently (i.e. between all 4 data sets) provide the best correlation. Table 5.2 shows the results of such an experiment for SSEB; the patterns are almost identical for the other data streams.

Table 5.2. The effects of the weighting scheme in equation (5.6) on cross correlations of SSEB demand with effective temperature

<table>
<thead>
<tr>
<th>( m )</th>
<th>0.1</th>
<th>0.2</th>
<th>0.3</th>
<th>0.4</th>
<th>0.5</th>
<th>0.6</th>
<th>0.7</th>
<th>0.8</th>
<th>0.9</th>
<th>1.0</th>
</tr>
</thead>
<tbody>
<tr>
<td>( r )</td>
<td>-0.75</td>
<td>-0.83</td>
<td>-0.88</td>
<td>-0.90</td>
<td>-0.91</td>
<td>-0.91</td>
<td>-0.90</td>
<td>-0.88</td>
<td>-0.86</td>
<td>-0.83</td>
</tr>
</tbody>
</table>

Table 5.2 shows clearly the optimal values of \( m=0.5 \) and 0.6. We are at liberty to choose either, though when taken to 3 decimal places \( m=0.5 \) is slightly better. This is the most widely used value elsewhere. In particular, it is worth noting that this TE formulation offers a highly significant (in excess of 99%) improvement on TA alone. That is, Fisher's Z transformation confirmed that the correlation with \( m=0.5 \) was significantly higher (>99%) than either end of the \( m \) scale in Table 5.2. (\( m=0 \) implies infinitely sluggish response, \( m=1.0 \) means no delay). Table 5.2 was constructed using deweeked data, since inclusion of the
weeklies hides any lag effects which we are experimenting with via m in equation (5.6).

The version of equation (5.6) when \( m = 0.5 \), i.e. assigning equal weights to \( TA(i) \) and \( TE(i-1) \), will be the one used here. When expanded, equation (5.6) represents an exponential decrease in the importance of previous day's TA. This satisfactorily reflects the general inertia in the response system, while still preserving the greater importance of today's TA. The time constant (efolding time) is approximately 1.5 days, i.e. the lag at which the contribution of previous day's TA decays to within 1/e of 0.5 is 1.5 days. The thermal lag factor due to delay in customer response is therefore of this order. TE is thus an exponentially smoothed or weighted TA formulation which takes account of the sluggishness of consumers in responding to TA. Though logically arrived at here, TE is also the solution of a first order lag equation in TA (see Davis, 1958). TE has found some success in modelling applications within the Power industries, after its introduction by Davis (1958), though Regional Boards vary their weighting factors to suit local responses. Most Boards use \( m = 0.5 \) in their formulation.

5.9.1.3. PHYSICAL ARGUMENTS IN DEFENCE OF TE

The TE parameter can be further defended physically since it also embraces the concept of thermal lag in buildings themselves. There is a time lag or inertia in the response of buildings to TA due to heat storage in the building fabric. It is important not to neglect the thermal capacity of buildings in this respect (see, e.g., Pratt and Weston (1951)). The conduction of heat across walls is controlled by thermal conductivity, wall thickness and material, amongst other factors, but also by the temperature gradient across the walls. To maintain a comfortable indoor microclimate, heating is used by an amount proportional to this gradient.

The use of a lagged temperature variable also becomes necessary when one considers sudden temperature changes. The demand response system takes of the order of a day (from the
evidence in Table 5.2 and the efighting time/thermal time constant) to respond in terms of fabric heat storage and also inertia in actual heating, especially storage heating. Though buildings do cool overnight, lags of the order of one day have been discovered elsewhere. For instance, a value of 24 hours was proposed by an official committee (HMSO, 1955) as applying to the majority of buildings, though outhouses and intermittently heated buildings would behave rather differently. Similarly, a sudden thaw/ mild outbreak following a cold spell, leaves buildings cold for of the order of one day.

In pursuit of a suitable and physically justifiable temperature statistic, then, a lag in customer response has been identified here. The exponentially smoothed or lagged temperature parameter is physically reasonable therefore and will be adopted as the working model temperature variable hereafter.

5.9.2. WINDCHILL (COOLING POWER OF THE WIND, CPW)

5.9.2.1. THE PHYSICS AND COMFORT TEMPERATURE

It seems reasonable to expect wind to influence consumption, since strong winds will increase heat dissipation from buildings, ventilation and air changes in a room. Interior heat losses will therefore be accelerated. Yet wind correlates very poorly with demand (shown later). This is because its effect is being swamped by temperature. Clearly, therefore, we must seek a different approach.

Several ways of uncovering the influence of wind were experimented with. The statistic to be presented here was constructed and developed to be consistent with the literature and the physics, as well as being statistically sound. We are thus trying to put the statistical parameterisations on a firm physical basis.

It does seem very likely that wind has an effect but not in isolation. It almost certainly interacts with temperature in a way that affects our perceived thermal comfort or how cold we feel, and in a way that controls ventilation (air changes). Its effect should not, therefore,
really be separated from TA, since high U and low TA will make the day feel colder than very low TA and small U. The problem now becomes one of deciding on a suitable TA parameterisation to combine with U. This will now be argued.

It seems sensible on physical grounds to expect domestic consumers to demand a higher heating requirement the more temperature deviates from some "comfort" level. This suggests (TCOMF-TA) could form the basis of a temperature parameter, where TCOMF is the "comfort temperature". This comfort level is very personal, being dependent on many complex and inextricably linked factors. These include level of activity, clothing, ventilation, building occupancy patterns, humidity and passive solar radiation. It is also controlled by more subtle physiological and psychological influences such as perceived illumination and dullness, rain, health, and various little-understood lag effects.

However, many studies have shown spatial and temporal average comfort levels to lie within a narrow band of 18-21 deg C. Human bio-meteorology and comfort is a field of its own and the reader is referred to Humphreys (1974, 1976), Leach (1981), Hunt and Steele (1980), WMO (1964) for further details.

The rate of heat loss (Q) from a flat surface obeys a general power law of the form:

$$Q \propto (TS - TA)^{**C}$$  \hspace{1cm} (5.7)

where: TS is temperature of flat surface;
TA is temperature of surrounding medium;
and C = 1 for linear Newtonian cooling

Note the similarity of this expression with that for heating degree days, equation (1.1). Now, C=1 is the only physically reasonable value, since heat transfer across walls, etc. depends linearly on the horizontal temperature gradient across them (Newtonian cooling). Such a law results in an exponential decay in the temperature difference across the walls. This idea is related to thermal conductivity or
transmittance coefficient \( (c) \) in the following heat flow equation:

\[
d\frac{Q}{dt} = -cA \frac{dT}{dx} \tag{5.8}
\]

where: \( A \) is area; \( \frac{dT}{dx} \) is the temperature gradient; and \( \frac{dQ}{dt} \) is rate of heat flow (heat flux density, W/m²)

The thermal conductivity \( (c) \) is sometimes referred to as a "U value" in architecture and building research literature; a typical value is 1.0 \( \text{W.m}^{-2}.\text{°C}^{-1} \) for the walls of a modern house. The Building Regulations stipulate maximum values of 1.7 and 4.5 \( \text{W.m}^{-2}.\text{°C}^{-1} \) for walls and windows respectively (BRE, 1975).

The rate of heat loss \( (Q \) in equation (5.7)) is proportional to heating requirement. Extending this analogy, with the flat surface being the building itself, \( \text{TCOMF-TA} \) would seem intuitively attractive and physically appealing to combine with wind \( (U) \). Since \( \text{TA} \) is the exterior temperature, \( \text{TCOMF-TA} \), say \( dT \), is the difference between interior and exterior temperatures. Experience has shown that power requirement varies with \( dT \). How this enhances heat loss will depend on windspeed (via ventilation and air changes). Hence the term \( UdT \) has arisen from time to time in the literature (e.g. Lacy, 1951), but was invalidated here for reasons which will become evident as we progress.

This "departures from comfort" concept appears meteorologically satisfactory. Rose (1949) found \( \text{TCOMF}=18 \text{ deg} \) C to provide the best fit when regressing \( \text{TCOMF-T} \) on gas demand (no wind of course). (Incidentally, base load could be found by extrapolating such a regression and solving for \( T=\text{TCOMF} \)). The higher \( \text{TCOMF} \) discovered in more recent work improves the fit by recognising the higher comfort levels people desire these days, and their greater affluence than in 1949. Hunt and Steele (1980) also show the comfort levels required by people to be rising due to their developing affluence and improving standards of living.

The definition of a "comfort temperature" forms the basis of the "degree days" approach too, where its
determination is also arbitrary (Chapter 1). See, for example, Mayer and Benjamini (1978), Guayle and Diaz (1980), Comte and Warren (1981), Warren and Leduc (1981). We will retain the \((TCOMF-TA)\) statistic for further use (for combination with a function of \(U\)).

5.9.2.2. THE WINDCHILL STATISTIC

It would seem from previous considerations that a worthwhile task would be to incorporate wind into this temperature statistic in some way. Retaining wind as a separate parameter would make it necessary to include wind direction effects (and their seasonal dependence, e.g. cold easterlies in winter). When \(T>TCOMF\) one would expect wind to have no effect or cooling power. It is only when \(T<TCOMF\) that wind will increase heat dissipation from buildings and increase demand by an amount proportional to the departure of \(TA\) from \(TCOMF\). This simultaneous control by \(TA\) and \(U\) suggests a combined parameter of the form:

\[
CPW (WINDCHILL) = \begin{cases} 
(TCOMF-TA) \cdot U^k & \text{when } T<TCOMF \\
0 & \text{otherwise}
\end{cases} \quad (5.10)
\]

where: \(CPW\) is cooling power of the wind;
\(k\) is some power of windspeed, as yet undetermined;
\(TCOMF\) is comfort temperature, as yet undetermined.

Though logically derived here, this explicit functional combination of \(U\) and \(TA\) is consistent with other experiments on heat loss from bodies exposed to wind, and is entirely consistent with the literature and the physics. Note that \(TA\) is used for combination with \(U\), and not \(TE\). This is because \(U\) will affect demand in conjunction with actual temperature (via its interaction as windchill) more intimately than with any other temperature. The power of windspeed is necessary because the interaction of \(U\) with temperature, on demand, is most probably not linear. Determination of \(k\) will be considered shortly.

To maintain a comfortable indoor microclimate, interior temperatures must be maintained at \(TCOMF\). Hence
heating is used to counteract wind induced heat loss. The windchill formula in equation (5.10) is thus an expression of perceived temperature (thermal comfort), i.e. how cold we feel. It also has an effect on ventilation, as we shall see. Both aspects will influence energy usage. The statistical properties of this parameter (distribution, temporal coherence, etc) will be discussed after we have obtained values for k and TCOMF in Chapter 6.

Windchill in a more general sense is an important concept in many areas of meteorology, e.g. mountain weather, biometeorology, vegetation physiology and microclimate. There are several interesting windchill applications in mountain weather, for instance Steadman (1971), Baldwin and Smithson (1979), Siple and Passel (1945), Barton (1981). Several other human comfort indices and empirical comfort equations have been developed elsewhere, for both tropical and temperate climatic regimes. These involve humidity, wet bulb temperature, windspeed, and various effective temperatures (not like TE), and are rather different from formulations here. Various charts of thermal stress/human danger zones have been compiled which, though very interesting, are outwith the scope of this discussion. See, for examples, Tout (1977), Lind (1964), Foord (1968), Brooks (1950).

5.9.2.3 VENTILATION AND AIR CHANGES

One would expect draught-induced demand sensitivity to vary with CPW, particularly in winter. Infiltration of air and ventilation rate are the important factors causing internal heat losses in wind conditions, rather than increased heat transfer at external surfaces (Davis, 1958). The experiments of Parsons (1949) on heat transmissions through walls show the effect of wind to be negligible. Ultimately only heat transfer by free convection at external surfaces matters. Either way, interior microclimate is an important consideration for fuel usage triggered or reactivated by draughts or excessive ventilation/air changes. Ventilation rate can be measured using Infra-Red techniques to measure diffusion of trace gas such as nitrous
oxide (e.g. Warren, 1976). The ventilation rate (=leakage or replacement rate) is then the fractional (%) rate of change of gas concentration over time (m**3/sec).

The number of air changes per hour (ach) in a building, or ventilation rate, is approximately a linear function of windspeed, see Dick (1949) and BRE (1975). In Britain, 0.5 ach is an average value for a well insulated draught-proof house. Bruce (1982), in a paper read before a Wind Symposium at Edinburgh University, confirms that infiltration varies linearly with windspeed for individual houses. More importantly, ventilation rate (as measured by air changes) is related to fuel consumption. This linear relation of air changes and windspeed suggests that $k=1$ in equation (5.10). This value has been used in several other studies on the fuel requirements of buildings: see, for example, Lacy (1951), Weston (1951), Dick (1949).

We are referring here to natural (free) ventilation and not forced (mechanical) ventilation (e.g. fans). Natural ventilation includes infiltration (draughts) through doors, windows, and by warmed air escaping elsewhere. A BRE Working Party Report in 1975 suggests domestic heat loss due to ventilation accounts for about 20% of total heat loss, though this will vary with insulation and exterior windspeed. BRE (1975) take ventilation loss to be 100 W/deg C, for a moderately ordinary family house. A minimum air change rate of 0.5 to 1 ach is needed in the heating season in homes, schools and offices, etc (BRE, 1975). This is to remove smoke, body odours, carbon dioxide, etc. Conductive (fabric) heat losses through the structure (floors, windows and roofs) are also important.

Alternatively, $k=0.5$ in equation (5.10) for convective heat losses from cylindrical wires and bulbs, as shown as long ago as 1923 by Hill. Heat losses from human bodies exposed to wind are also given by $k=0.5$, with TCOMF=36.7 deg C. Equation (5.10) therefore supports an analogy with the cooling of human bodies, where the body here is the building itself. Brooks (1950) also claims that wind-induced heat loss from buildings varies roughly with the square root of windspeed, though he was referring to conductive losses.
enhanced by wind, not ventilation.

On the other hand, the pressure forces on the side of a building are proportional to the square of windspeed, and one would perhaps expect ventilation (and hence energy use) to be linearly related to such forces. Hence $k = 2.0$ is yet another physically sensible possibility.

There is no clear cut advice in the literature on this, so the uncertainty regarding $k$ and $TCOMF$ led, in this study, to all combinations being tried. Those giving rise to the best correlation with residual errors from temperature alone (to be explained in Section 5.13) were chosen for the windchill statistic (equation 5.10).

The most popular values are $TCOMF=18$ deg C and $k=0.5$. These are the ones currently being used by the CEGB for retrospective weather correction of past demands, and for forecasting. In a sense, we are testing these already accepted values, though it is believed that how this will be performed is unique.

Other windchill formulations were derived and experimented with here, but were felt to be invalid. For instance, some Area Boards think it sensible to introduce a critical or threshold windspeed (say $U_0$), below which any effects on demand are small or possibly masked by other factors. There wind parameters would look something like $(U-U_0)*T$ or $(U-U_0)*(TCOMF-T)$ or $U*dT$. N. Thames use 12 knots as the lower cut-off windspeed, E. Midlands and S. E. Gas Boards use 8 knots. The wind is assumed to have no cooling power below these sharp cut-offs, however low the temperature is (termed the "zero wind problem" here).

Piggott (1980), in a paper on Box-Jenkins gas demand forecasting presented to the Royal Statistical Society in London, suggested an 'upper' cut-off at 15 knots (all $U>15$ knots assumed to be equivalent to 15 knots). If either threshold idea is a reasonable supposition, then one of them will manifest itself in the later determination of the value of $k$ in equation (5.10), though CPW cannot cope simultaneously with both upper and lower cut-offs. Other functions of $U$, taking account of decreasing sensitivity at very low or high $U$, are possibilities.
The CPW statistic used in this study avoids the necessity of additional description of direction effects, by combination with TA (cold winter Easterlies, etc). Interestingly, N. Thames still prefer to build direction in separately. Also, any windchill should logically include departures from TCUMF, not just TA, otherwise the effect of similar U is the same at all TA (as in U*T). Equation (5.10) does retain the zero wind problem (CPW=0 if U=0), but since CPW will be added stepwise after TE in our model, this is not important, as we now show.

5.9.2.4. WINDCHILL EQUIVALENT TEMPERATURES

An alternative formulation which attracted the most attention here is the idea of "equivalent temperature". This turns out to be just a special case of the CPW formulation presented here. The notion of wind-corrected temperatures has been hinted at. Some energy authorities wind-correct their temperatures before prediction. The resulting temperature is referred to in windchill literature as "windchill equivalent temperature" (WET) or "wind corrected temperature" (WCT), see Steadman (1971). This temperature is that perceived in the absence of any wind. It is effectively the temperature at which motionless air would produce the same sensation of cooling as the actual conditions. As examples, W. Midlands and Eastern Gas Boards use 18 knots as equivalent to -1 deg C. If we denote such constants generally by \( w \) (deg C/Knot), then WCT or WET would be given by:

\[
WCT = WET = TA + (U*\omega) \tag{5.11}
\]

...so long as \( w \) is non-linear in temperature.

When \( U=0 \) there is no additional cooling effect of the wind, and WET collapses to just TA. The product \( U*\omega \) is sometimes loosely referred to as a "chill factor", particularly in American literature.

Like the CPW statistic, WET combines U and T in the same statistic. For this approach, one needs to know how
many knots of wind have the equivalent effect on demand as 1 deg C. This was investigated here by a technique to be covered later, though exactly how this empirical relation is obtained is somewhat arbitrary. This is one of the drawbacks of WET, and is partly why here CPW is preferred to WET.

In the model to be derived, the CPW statistic will be added after TE in a multivariate scheme. It thus represents the additional effect of windchill after TE has been accounted for. We thus have two distinct parameters: TE and CPW. A disadvantage of WET in comparison is that being one parameter it hides the separate physics of windchill and temperature. We cannot therefore evaluate their independent effects. This is not a problem in the multivariate combination of TE and CPW.

Though CPW is a rather fundamental quantity, it cannot replace TE. It cannot be used alone since it is zero when U=0, and when T>TCOMF. Addition of CPW after TE overcomes this zero wind problem. The resulting model to be used here still represents (though not strictly so) a form of wind-corrected temperature (or WET), this time given by:

\[ WCT = WET = TE + \left( T_{COMF} - T_{a} \right) \frac{U}{k} \]  \hspace{1cm} (5.12)

Once again for zero U, WET becomes TE.

Conveniently, equation (5.12) collapses to something vaguely resembling equation (5.11) when k=1.0. The original WET in equation (5.11) is therefore almost a special case of the proposed formulation (equation (5.12)). Since this comparison is not strict, no further reference will be made to WET in the TE and CPW multivariates. There are other more subtle reasons for discrediting equation (5.11), other than those already given. Perhaps the most intuitively obvious is the poorer correlations with demand when using it.

The CPW derived here (equation 5.10) will be adopted as the windchill statistic later, after determination of k and TCOMF. It will then replace wind.
5.9.3. THE EMPIRICAL SRV (MISERY) INDEX

5.9.3.1. JUSTIFICATION OF THE PARAMETER

Temperature and windchill, then, are the most important atmospheric factors affecting energy demand, due to their control on the heating load. It was convenient to partition this heating load into a thermal storage component controlled by the direct effects of temperature (conductive heat loss), and a wind-induced ventilation heat loss (windchill). For electricity there is another important component. This is lighting. The demand for lighting varies in a quasi-predictable fashion through the year in response to the astronomical forcing of sunrise, sunset and hence daylength. This affects domestic, commercial (shops, schools, offices), industrial, street and public lighting. See Crisp (1976) for fluorescent lighting in offices and schools. More of concern to us, it also varies much more randomly (or so it seems) on the daily time scale, being governed also by such atmospheric variables as sunshine, cloud cover, rainfall and visibility (e.g. fog), since these determine daylight illumination. For instance, a sudden thunderstorm darkening the sky over a large built up area or conurbation can cause sudden surges in lighting demand. Such changes in illumination should be anticipated by the electricity suppliers. Similarly, office lighting in, say, Central London or Manchester is very sensitive to how dark the sky appears. Artificial lighting appears to be most sensitive at dusk, especially in cities and during heavy cloud, rain or fog.

For both electricity and gas, furthermore, influences of this nature are inextricably mixed in with various often rather subtle psychological and social effects on consumer behaviour. These include perceived dullness or brightness (i.e. "sunniness"), "raininess" (people stay indoors using fuel not otherwise used), and how the weather feels in general. These are little understood but it is physically sensible to expect them all to act in combination and to be highly significant on occasions.

This justifies an overall empirical combination of
sunshine, rainfall duration and visibility into a synthetic index to test this hypothesis. These variables were all assumed to contribute equally to the overall weather, and so were given equal weights and divided by their respective ranges. Such an index was termed the SRV (sun-rain-visibility) index, where SRV (for Scotland) is given by:

\[ SRV = \left(2 - \frac{SUN}{10.2} + \frac{RD}{1230} - \frac{VIS}{58.4}\right) \times 33.33 \quad (5.13)^a \]

Since no RD or VIS are available for the S.E., for consistency SRV for England is defined by:

\[ SRV = \left(1 - \frac{SUN}{10.7}\right) \times 100 \quad (5.13)^b \]

The offset and scaling factors were included to force this dimensionless index to vary between 0 and 100 (in both cases). It will be at its maximum (100) when rainfall duration is high and both sunshine and visibility are low, and vice versa (similarly for the S.E. but with SUN only).

5.9.3.2. PSYCHOLOGICAL/SOCIAL AND PHYSICAL EFFECTS

The sun-rain-visibility index can intuitively be thought of, and therefore informally referred to, as a "Misery" index, for it sums up how depressing, dark, wet, or miserable the weather may feel (which is why SUN was explicitly made -ve). This is its greatest advantage, for it manages to combine the relevant variables (by scaling them) into a measure of how "nice" (pleasant) or "gloomy" (depressing) the day is, which is important with respect to perceived thermal comfort. It is thus a measure of the overall mood of the weather, and hence how we feel in general, as well as being an approximation to daylight illumination. This is why each parameter was not individually fitted, as indeed they could have been, being linear. Clearly, SRV (misery) is completely reversible according to sign, when one would perhaps refer to it as a "Cheer" factor. Either way, it will be shown to exercise a significant control on fuel usage.

It is clear now why rainfall duration was chosen in
preference to actual rainfall amount, since frequency of rain, or how long rain lasts, affects whether people stay indoors, more than how much actually falls. The comparison of steady continuous light or moderate frontal rain (e.g. ahead of a slow-moving warm front) with showery but heavy convective rain (e.g. an unstable showery NW Polar Maritime flow) makes this point clear.

Rainfall will also exercise an indirect non-behavioural control. The effect of rain on the exterior fabric of buildings will be to enhance heat loss at external surfaces. Heat transfer across the walls will be encouraged mostly due to evaporative cooling of the outside wetted surface. This effect is likely to be small in relation to the conduction heat loss across the walls. Rainfall also very indirectly takes account of perceived dampness and humidity in a crude way, though this must be a small effect on fuel usage. It does have the more significant effect of keeping people indoors (hence using energy), and also helps to reduce perceived daylight, especially heavy rain.

Sunshine, too, is clearly very influential, for it not only controls daylight illumination but also our perceived temperature. This part of the index, as well as including brightness, also attempts to encompass this perceived temperature by the action of direct sunlight. Sunshine takes indirect account of cloud cover, being strongly negatively correlated with it. Another significant effect of sunshine is direct heating of building fabric and hence reduction of conductive heat loss.

Yet another important effect is that of passive solar radiation (through windows, etc), as well as encouraging people to go out of doors and hence use less fuel. For those that do stay inside their homes, sunny weather invokes a feeling of warmth by passive energy gains. This is particularly true of south facing offices and homes in winter, when the sun’s elevation is low, allowing maximum penetration of passive solar radiation. Hence aspect and interior microclimate in dwellings, offices and flats are serious considerations. See Loftness (1978) for sunshine in windows and other interesting aspects of architecture,
climate and sunlight interception.

Visibility helps to decide the effective illumination, but too has a psychological effect via perceived dullness/gloominess, etc. To pick out just two extreme examples: compare a dull, cold and foggy situation (e.g. East Coast sea fog or "haar") with a crystal clear but exhilaratingly cold Arctic Continental flow with excellent visibility. Note that we are using only daytime visibility values, i.e. sunrise to sunset, since visibility is assumed to be totally subordinate in darkness hours.

5.9.3.3. HYSTERESIS LOOPS AND CATASTROPHE THEORY

As will be demonstrated in the case studies, the SRV parameter correlates encouragingly well with forecast errors when using TE and CPW. This is very rewarding, considering one would really expect to be at the noise level once the relatively massive effects of TE and CPW have accounted for most of the variance in demand. It is at this level that one would expect various hysteresis effects to start to come into operation, e.g. fires or lights staying on once TA or daylight illumination has recovered to its original value. When perceived temperature is falling, heating is switched on, but when TA rises to the previous comfort level it is not switched off. People have different comfort thresholds or critical jumps according as whether TA is falling or rising. The same phenomenon arises in lighting with effective illumination. As daylight fades, people switch on artificial lighting but have a tendency to leave it on once the sky brightens again after a dull spell. These points suggest applications of catastrophe theory, to understand such sudden discrete changes. These hysteresis loops in consumer response could only be uncovered with hourly data. Here, then, one is beginning to see microscale responses (within offices or homes) discussed in Chapter 4.

5.9.3.4. STATISTICAL PROPERTIES OF SRV

The SRV series for Scotland is given in Figure 5.9, accompanied by its probability distribution and correlogram. The SRV index is seen to be approximately normally
Figure 5.9: a) The SRV index for Scotland: 1 Jan – 31 Mar 1979
b) The correlogram of the Scottish SRV index
c) The probability distribution of SRV
distributed (Figure 5.9c), despite its constituent variables being somewhat skewed (Figure 5.7). It is thus valid to use it in the normal way in future statistical analysis. It is rewarding to note that the individual use of SUN, RD or VIS would have been restricted by their lack of normality (i.e. skewness), and would have rendered their application in certain parts of the analysis invalid. The SRV record itself shows some very short term persistence, days with high misery tending to occur in groups, though notable sudden changes do occur (Figure 5.9). This weak serial correlation does not show up in the autocorrelation function.

It is important to realise that the factors in the SRV index will interact; this is one of the advantages of combining them functionally, since it is very difficult to separate them anyway. The overall effect of them is the weather as a whole. This is what determines demand through perception of the environmental conditions (daylight and weather mood) in relation to thermal comfort. This was one of the greatest motivations here for its development. Additionally, the SRV index shows some interesting relationships to synoptic situation and residual/forecast errors. It is thought here that this parameter is novel.

Now that we have derived the working model weather variables, we can proceed to the heart of the development of the model itself.

5.10. BANK HOLIDAY ADJUSTMENTS

Jan 1, 1979 was a bank holiday in England, Jan 1 and 2 were in Scotland, see Figures 5.2 and 5.3. Bank holidays are special days that must be dealt with separately, or else spurious correlations will result. Other local, public, school or industrial block holidays are difficult to adjust for on a regional daily basis. With many years data, holiday factors could be determined from long term means.

The procedure devised here for dealing with bank holidays is to linearly interpolate between the 2 adjacent values. As it stands, this would obviously be confused by weather effects, and so these adjacent values were temperature corrected first, using the equation:
\[ TCV = RAW - b \cdot TDEV \quad \text{(5.14)} \]

where: \( TDEV = TA - \bar{TA} \) (mean TA for whole period);

TCV is temperature corrected value;

and \( b \) is obtained from regressing \( RAW - RAW \) on \( TA - \bar{TA} \)
(excluding bank holidays)

After interpolation between these 2 temperature corrected values, the temperature dependence of the bank holiday can then be added back in.

The procedure requires 2 adjacent values. For Jan 1, 1979 there were no data for 31 Dec 1978. The best estimates for more normal values to replace the anomalously low bank holidays were, in that case, calculated from a straightforward linear regression of demand vs TA (again excluding Jan 1 and 2). The new bank holiday value (BHV) is given by:

\[ BHV = a + b \cdot TA \quad \text{(5.15)} \]

More complex iterative procedures for separating holiday and weather effects are possible, but the above methods are perfectly adequate for our purposes. The atmosphere clearly doesn't have any bank holidays and the weather data requires no such adjustments.

5.11. REMOVAL OF THE WEEKLY CYCLES (DEWEEKING)

The weekly cycles in energy consumption are so important and non-weather dependent as to necessitate their removal. Various methods are available (and were tried) for removing such a regular periodic oscillation. These include % deviations from day of week means, 7-point moving averages, weekly sine waves, seventh-order differencing, or the more sophisticated Census Bureau "XII" routine used by the Department of Energy (see Shiskin, 1967).

The problem common to all techniques is that we are trying to see regular oscillations against a noisy background. The procedure adopted here is directly analogous to deseasonalising monthly data (see Chapter 3 for its
justification). For alternative methods see Kendall (1973), Spiegel (1972).

The raw daily data were firstly divided by the weekly mean for that week, yielding "weekly indices" (>1 weekdays, <1 at weekends). The means of these weekly indices or "day of week corrections" for all Sundays, Mondays, etc., were then computed. Finally the raw data were divided by the day of week correction (DOWC) appropriate to that particular day.

The technique treats all weeks identically, hence none of the temperature dependence will be affected. Some of this dependence was initially obscured by the weekly waves. The technique has the effect of raising weekend values and lowering weekday demands. The temperature traces obviously show no weekly wave and need not therefore be treated in this way. It was felt here that this "average percentage" method, as defined by Speigel (1972), is superior to other methods, since the DOWC's express demand as a relative (proportional) percentage of the weekly mean.

Before the method could be applied there was an additional complication. The raw demands had to be firstly temperature corrected just temporarily, i.e. for the purpose of this routine only, this dependence being added back immediately after deweeking is complete. This necessity arises partly from a hidden sublety in the daily sensitivity. There is a well marked daily variation of sensitivity to TA (as measured by r) through the week. This is often not entirely systematic but with highly significant (>95%) variations between days. As will be shown in the case studies, sensitivity is usually higher at weekends (showing the dominance of the domestic sector).

This would, if neglected, lead to instability in the DOWC's which would result in spuriousness creeping into any further analysis. The series were temperature corrected or adjusted applying equation (5.14). Unfortunately, the data sets were too small to obtain statistically reliable daily b's, and so an overall blanket b value for the whole 90-day data set was used.

The temperature adjusted demand series will more
realistically reflect the underlying weather-insensitive variation of base load through the week. Without adjustment, the chance occurrence of, for example, 2 very cold Wednesdays in these 13-week records, would result in undesirably erroneous DOWC's. Similarly, the DOWC's would be excited by the chance occurrence of a run of fine weekends. The daily sensitivity variation of the temperature corrected array (as measured by r) was, as anticipated, much more uniform. This confirms the need to perform this temperature adjustment beforehand (and thence to add it back in after deweeking).

Figure 5.10 shows the Acf's of raw and deweeked data superimposed for SSEB. The 7 day cycle in the original raw data is clear from the Acf, but vanishes on deweeking. The raw (RAW) and deweeked demand (DWD) for SSEB were put through the spectral analysis described in Chapter 2, and Figure 5.10 gives their wave spectra. The peak at wave 13 in the raw data, representing the weeklies, disappears on deweekization. This is purely an initial example for SSEB; Chapter 6 will provide a more complete discussion.

Hence our deweeking method is satisfactory, though there is still plenty of serial correlation around, as evidenced by the Acf failing to dampen, and the relatively large low wavenumbers (Figure 5.10). This brings us conveniently to the next stage in the development.

5.12. REMOVAL OF SEASONALITY AND LOCAL TREND

We have already remarked on how demand varies on the inter-weekly time scale in response to cold/warm spells and blocking/progressive periods. There is also a general decrease as the year progresses during these 3 months, especially towards the end, due to the annual cycle. Both these components together we shall term "local trend and seasonality", or often more simply "seasonality". These are distinct from the true base load, for they are weather susceptible on this time scale by definition, but can be thought of as the underlying, slowly varying general trend.

Since the existence of these components has meant that there is still some persistence remaining after deweeking
Figure 5.10: a) The Acf's of raw and deweeked SSEB demand
b) Wave spectrum of raw SSEB demand
c) Wave spectrum of deweeked SSEB demand
It is desirable to remove this more systematic, quasi-deterministic part of the load. Examining deviations from this (i.e. residuals) will allow the exploration of the short term (i.e. daily) response to TA, within cold spells, and within the general demand levels for that time of year. It is these intra-weekly fluctuations which should concern us for daily forecasting, for this is the real short term sensitivity, which is more erratic and inherently less predictable therefore, being forced by more sudden changes in atmospheric conditions. Since both deweeked demand and raw TE series exhibit this seasonality, it must be removed from both.

The piecewise linear interpolation technique, introduced in Chapter 3, will be applied to achieve this end. Reasons for rejecting other approaches to seasonal adjustment were detailed in Chapters 2 and 3. These included differencing, eigenvectors, polynomials and Fourier analysis, all of which suffered from either problems of physical interpretation or persistence. The interpolation method derived here does not suffer from either of these. In this scheme, individual daily values of seasonality are interpolated linearly between the weekly means, taking the weekly means as being representative of the mid point of each week (Wednesday). The linear interpolation equation used to deseasonalise the DWD and TE arrays in this way was:

\[ \text{LIN} = \text{WM}_1 - \text{ND} \times \frac{(\text{WM}_1 - \text{WM}_2)}{7} \quad (5.16) \]

where: LIN is level of seasonality (and local trend);
WM is weekly mean;
ND is number of day (0..6, starting Wednesday).

The deviations of DWD and TE (residuals) from their respective seasonals represent deseasonalised data, and will be termed DDEV and TDEV respectively.

It is not possible, initially, to calculate seasonals for the first 3 or last 4 days, since there are no weekly means outside the array length from which to interpolate. This also arose with monthly data in Chapter 3. Imaginary
weekly means for the week proceeding the first and following
the last were therefore computed by linear extrapolation.
Equation (5.16) could then be applied as before.

In a wider sense (that is, for much longer time series), this technique also copes with "long-term" trend
(i.e., inter-annual variability) since it interpolates
between "local" weekly means.

As we will witness in the case studies, the stepwise
interpolation procedure provides a much more accurate
representation of seasonality and local trend than any other
technique. Similarly, it will also be shown that this
approach removes almost all the persistence, and the
residual traces are therefore almost stationary. Hence any
residual correlations will reflect the short-term weather
dependence of the non-autopredictive component of demand on
weather.

So, to remind us of the present state of the model
decomposition of the series, after taking deviations from
seasonals we have:

\[ DWD = \text{LIN} + a + b \cdot \text{TDEV} + c \cdot \text{CPW} + d \cdot \text{SRV} + \text{error} \quad (5.17) \]

Now that we have removed weeklies and seasonality to
obtain deviations, we will explain how the constants in CPW
(equation 5.10) are arrived at from residual errors.

5.13. CONSTRUCTING WINDCHILL FROM RESIDUAL ERRORS

The residual records, being quasi-
may now
be cross correlated to obtain a measure of the intra-weekly
sensitivity (short-term weather dependence), i.e.

\[ \text{DDEV} = a + b \cdot \text{TDEV} + \text{error} \quad (5.18) \]

As explained in Section 5.9.2.4, it will be very
worthwhile and physically reasonable to add CPW after TE.
The uncertainty regarding \( k \) and \( \text{TCOMF} \) in equation (5.10) has
been emphasised. We now want to maximise the further
variance in \( \text{DDEV} \) explained by CPW after TE has accounted for
so much. It is totally justified therefore to regress all
combinations of \( k \) and \( \text{TCOMF} \) with the residual errors from
TDEV alone (actual—predicted DDEV). This is the crucial step in the windchill factor derivation, and represents an "empirical optimisation" approach. From equation (5.18), such residual errors (RE) would be given by the following equation, and we are saying they are proportional to CPW:

\[ \text{RE} = \text{DDEV} - (a + b \cdot \text{TDEV}) \propto \text{CPW} = \left( \text{TCOMF} - \text{TA} \right) \cdot U^k \]  \hspace{1cm} (5.19)

The CPW formulation showing the highest cross correlation with RE is the optimal formulation to add after TE.

TCOMF was allowed to vary from 10 to 25 deg C in discrete steps of 1 deg C. The wind exponent \( k \) was free to vary from 0.0 (no wind dependence) to 2.0 in steps of 0.1. These intervals provide us with a suitable compromise between a fine and coarse mesh grid for the resolution of the resulting correlation field. We would naturally hope for values of \( k \) and TCOMF that are statistically different from their neighbours in the correlation domain, and that are consistent with the literature and physics too. It must be remembered here that we are really testing the validity of the accepted values: TCOMF=18 deg C and \( k=0.5 \text{ or } 1.0 \). This part of the presentation will feature the use of computer graphics for the visualisation of the correlation domains as 3-dimensional perspective histograms.

After we have chosen the optimal CPW formula from residual errors, CPW will replace \( U \) and our model for the deviations will become:

\[ \text{DDEV} = a + b \cdot \text{TDEV} + c \cdot \text{CPW} + d \cdot \text{SRV} + \text{error} \]  \hspace{1cm} (5.20)

5.14. THE DYNAMIC AUTO PROJECTION SCHEME

To perform analyses of variance and examine residual errors of past data in the above way, as we shall see, is very instructive in trying to understand consumer response. This is really testing the model on itself, to see how well it predicts its own past. Seasonality can here be visualised as perfectly predictable and deterministic, for we have complete knowledge of the past (weekly means). When
forecasting, if future DDEV values (short-term weather dependence) can be predicted, then they can be added to the seasonal component for a final load forecast. In such circumstances, we would not know future seasonals, for the weekly means have not happened yet.

An autoprojection technique was derived here to predict future seasonals, using the previous weekly mean to extrapolate one day forward. The autoprojected seasonal component for the following day (DPROJ and TPROJ for DWD and TE) is given by the mean of the previous 7 days. The scheme is dynamic in the sense that the previous weekly mean is continually updated (every day in fact), so that such seasonals may drift with variations on time scales of one week or more. It takes weekly means so as not to encroach on the short-term sensitivity (as reflected by the deviations). To impinge on this would invalidate residual cross correlations. To retain weekly-mean units as defining seasonality is the only way to tease out this short-term sensitivity.

One can thus forecast future seasonals, how does one forecast future deviations from them? It is here that we will get involved with splitting the data set into halves. DDEV for the second half are predicted using model coefficients derived from the first half (deviations from seasonals therein). Hence we are testing the model on wholly independent data.

Even though one could model the first half using linearly interpolated seasonals, the nature of the projection method and its flexibility means one can just as easily backcast them for the first half, i.e. autoproject retrospectively. For statistical consistency, also, backcasted autoprojections for the first half would be preferable to interpolations. For the first week of the first half there is no previous weekly mean from which to autoproject. The simple weekly mean for the first week is used in that circumstance, for the first 7 days. Like interpolation, dynamic autoprojection can implicitly cope with long term trend. It can also be adapted to predict several days ahead, though this was not attempted here.
So, model coefficients in equation (5.20) are determined from the first half, using deviations from backcasted autopredictions. It is the residual errors of these deviations for the first half, that are cross correlated with various combinations of k and TCOMF in CPW.

The method does not split the data exactly into halves. To ensure a complete (integer) number of weeks for modelling the first half, it is the first 49 days (7 weeks) whose model coefficients are used to predict the remaining 41 days of the second half (almost 6 weeks).

This method is wholly operational and uses totally independent data to predict future values. It is therefore much more realistic. To predict values outside a given data set from coefficients obtained within it is the harshest (and most reasonable) test one could give to a predictive model.

5.15. THE FINAL TOTAL DEMAND FORECASTING EQUATION

The final demand forecast is obtained by adding back the forecast DDEV (inter-daily weather sensitivity) from equation (5.20), to the autoprojected seasonals and then multiplying by the DOWC, i.e.

\[
\text{FORECAST} = (\text{SEASONAL} + \text{DDEV}) \times \text{DOWC} \quad --- (5.21)
\]

Since this prediction scheme is intended to be wholly operational, the DOWC’s and the associated b’s (for temperature adjustment pre and post-deweeking; Section 5.11) are derived only for the first half. In addition, since the day-of-week-corrections were derived from a temperature-corrected array (Section 5.11), the initial forecast (= SEAS + DDEV) must be temperature corrected before multiplying by DOWC’s. After adding back DOWC’s, the temperature dependence is added back.

We must now step right back and form a broad picture, having focussed on details of the model development. The final complete forecasting equation now follows. A physical interpretation of terms is also provided for reference.
Equation 5.22: The final complete demand forecasting model

\[
E = (\text{SEASONAL} + a + b \cdot \text{TDEV} + c \cdot \text{CPW} + d \cdot \text{SRV}) \cdot \text{DOWC}
\]

\[
(2 - \text{SUN}/10.2 + \text{RD}/1230 - \text{VIS}/58.4) \times 33
\]

Annual Cycle Conduction Windchill. Misery. Weekly
+Local Trend Term (Ventilation Social/ Wave.
Air changes) Illum' (Base
Load)

SEASONALITY HEATING LOAD LIGHTING WEEKLIES

Equation (5.22) can be used as reference throughout Chapter 6, and is also reproduced in Appendix 2 to facilitate consultation/cross reference from elsewhere. It is maintained that all the sophistications and physics built into each parameter are both statistically and physically palpable and reasonable, since the treatment of their development was thorough. The variability of demand due to the weather is fortunately far greater than any source of error in the data or uncertainties in terms. Nevertheless, a total mathematical error analysis of the complete model will be undertaken in Chapter 6.

We are now in a position to move immediately on to the case studies, and their inter-regional comparisons.
CHAPTER 6

FORECASTING DAILY ELECTRICITY AND GAS DEMAND:
SOME SCOTTISH AND ENGLISH REGIONAL CASE STUDIES

6.1. INTRODUCTORY REMARKS

Chapter 5 described the development of the energy forecasting model in detail. This Chapter applies this to two Scottish and two S.E. English regional case studies. Since these Chapters are complementary the case studies require little introduction, this was given at the start of Chapter 5. In a sense, part of the daily case studies presentation has already been covered in Chapter 5, as examples interspersed throughout the derivation of the model, and the data itself was presented and discussed at length.

It is in these two Chapters that the statistical techniques described in Chapter 2 are at their most useful and revealing. Use of them is at its most creative here, and the results at their most rewarding and encouraging. Far fewer references will be given hereafter, only the results of the author's work using the mathematical/statistical model derived in Chapter 5. We can now start straightaway on these daily regional case studies.

6.2. DEWEEEKED DATA

6.2.1. DAILY VARIATIONS OF TEMPERATURE SENSITIVITY

The raw demand data have been presented in Figures 5.2 and 5.3. Let us now consider the deweeked data. Chapter 5 explained why it was necessary to temperature-adjust the raw series prior to deweekling (and thence to add back in the temperature dependence). This was partly because of the daily pattern of sensitivity variations to temperature. This pattern is of interest in itself, and is shown in the following Table.
Table 6.1: Daily variations in sensitivity of electricity and gas demand to temperature (as measured by r), for all four energy data arrays (raw data)

<table>
<thead>
<tr>
<th></th>
<th>SEEB</th>
<th>NTGAS</th>
<th>SSEB</th>
<th>SCGAS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Monday</td>
<td>-0.78</td>
<td>-0.95</td>
<td>-0.62</td>
<td>-0.73</td>
</tr>
<tr>
<td>Tuesday</td>
<td>-0.87</td>
<td>-0.88</td>
<td>-0.54</td>
<td>-0.31</td>
</tr>
<tr>
<td>Wednesday</td>
<td>-0.78</td>
<td>-0.75</td>
<td>-0.74</td>
<td>-0.71</td>
</tr>
<tr>
<td>Thursday</td>
<td>-0.84</td>
<td>-0.96</td>
<td>-0.65</td>
<td>-0.53</td>
</tr>
<tr>
<td>Friday</td>
<td>-0.87</td>
<td>-0.90</td>
<td>-0.71</td>
<td>-0.74</td>
</tr>
<tr>
<td>Saturday</td>
<td>-0.87</td>
<td>-0.88</td>
<td>-0.78</td>
<td>-0.81</td>
</tr>
<tr>
<td>Sunday</td>
<td>-0.84</td>
<td>-0.94</td>
<td>-0.74</td>
<td>-0.79</td>
</tr>
</tbody>
</table>

There is a highly significant (beyond 99%) variation in r through the week, though this is not entirely systematic. One can observe from Table 6.1, at least for Scotland, systematically higher sensitivity at weekends. This is probably due to the relative dominance of the domestic market at that time, industry being relatively subordinate. There is a higher overall temperature sensitivity for the South-East (explained later).

We now give the day-of-week-corrections themselves.

Table 6.2: The "day-of-week-corrections" (DOWC), and % variance explained by the weekly cycles.

<table>
<thead>
<tr>
<th></th>
<th>SEEB</th>
<th>NTGAS</th>
<th>SSEB</th>
<th>SCGAS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Monday</td>
<td>1.016</td>
<td>0.999</td>
<td>1.028</td>
<td>1.024</td>
</tr>
<tr>
<td>Tuesday</td>
<td>1.026</td>
<td>1.005</td>
<td>1.039</td>
<td>1.021</td>
</tr>
<tr>
<td>Wednesday</td>
<td>1.029</td>
<td>1.017</td>
<td>1.028</td>
<td>1.022</td>
</tr>
<tr>
<td>Thursday</td>
<td>1.049</td>
<td>1.043</td>
<td>1.037</td>
<td>1.033</td>
</tr>
<tr>
<td>Friday</td>
<td>1.045</td>
<td>1.032</td>
<td>1.028</td>
<td>1.016</td>
</tr>
<tr>
<td>Saturday</td>
<td>0.927</td>
<td>0.945</td>
<td>0.918</td>
<td>0.929</td>
</tr>
<tr>
<td>Sunday</td>
<td>0.900</td>
<td>0.956</td>
<td>0.917</td>
<td>0.950</td>
</tr>
</tbody>
</table>

% variance of raw data: 37% 10% 40% 21%
The DOWC's are clearly lower at weekends, and reach a peak about midweek (for England); these are the necessary values, then, to divide the raw data by to deweek them. Weekend demands are on average between 90% and 95% of weekly means, midweek about 103% to 105%. The weekly cycles are more pronounced for electricity, accounting for some 40% of the variance in regional daily electricity sales (more than double that for gas, Table 6.2). The mean amplitude of the weekly wave accounts for about 10% of the total load, on average. Hence they are an important cyclical effect.

Section 5.11 illustrated the effects of the deweeking scheme by spectral analysis and autocorrelation, and showed it to be satisfactory. Much further back, Chapter 2 used univariate superposed epoch analysis to expose the weekly periodicity in daily electricity consumption.

We may now proceed to the partial and multivariate cross correlation analyses to uncover physical (cause-effect) relations between deweeked data (DWD) and the model variables.

6.2.2. PARTIAL CROSS CORRELATION ANALYSIS

Table 6.3 presents the partial regressions of DWD with the meteorological parameters.

Table 6.3: Partial cross correlations of deweeked demand with weather variables, for the whole 90-day data sets (not deseasonalised)

<table>
<thead>
<tr>
<th></th>
<th>TE</th>
<th>U</th>
<th>SRV</th>
</tr>
</thead>
<tbody>
<tr>
<td>SEEB</td>
<td>-0.93</td>
<td>-0.21</td>
<td>+0.37</td>
</tr>
<tr>
<td>NTGAS</td>
<td>-0.90</td>
<td>-0.17</td>
<td>+0.27</td>
</tr>
<tr>
<td>SSEB</td>
<td>-0.76</td>
<td>-0.06</td>
<td>+0.19</td>
</tr>
<tr>
<td>SCGAS</td>
<td>-0.75</td>
<td>-0.05</td>
<td>+0.11</td>
</tr>
</tbody>
</table>

Coefficients exceeding 0.55 are significant at 95%.
From Table 6.3, TE is by far the most important factor. The first interesting inter-regional comparison concerns TE. Response to temperature is considerably higher for S.E. England. This interesting disparity between regions probably results from the differing load-mix between the regions, rather than different actual sensitivity. Scotland has a relative preponderance of traditional heavy industries in its load-mix, whereas in London and the S.E. the commercial and domestic sectors dominate more.

The effect of wind for both regions appears totally insignificant, and is negative, surprisingly. This arises from the positive multicollinearity of U and TE (see partial cross correlation matrix in Section 5.6.4); i.e. high U >> high TE >> low demand ( >> means implies). The SRV index correlates better with electricity than gas, as expected, due to lighting, but this too is weak. For Scotland, the individual cross correlations of SUN, VIS, and RD (i.e. the constituents of SRV) were all totally insignificant.

Despite the poor correlations of U and SRV, it will be conclusively demonstrated that these effects are sometimes crucial. Here they are being masked by the relatively massive and dominating effects of TE. Note too that we are still using U and not CPW, since we have not yet chosen CPW from residual errors.

6.2.3 MULTIVARIATES

Moving now to the stepwise multiple regression analyses, Table 6.4 shows the results of adding TE, U and SRV stepwise and in that order. Note that the following multivariate Tables are for deweeked demand (DWD) for the whole 90 days, and which is not deseasonalised as yet. See reference list of variables for abbreviations; all demands are in MWh, gas in 1000 therms (T.Th), b has units MWh/deg C or T.Th/deg C, c has units MWh/knot or T.Th/knot, and d’s units are MWh/SRV unit or T.Th/SRV unit.
Table 6.4: Complete stepwise multivariate analyses of deweeked demand with meteorological parameters

<table>
<thead>
<tr>
<th></th>
<th>SEEB</th>
<th>N. THAMES GAS</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>DWD vs....</td>
<td>TE</td>
</tr>
<tr>
<td>Multiple r</td>
<td>-0.93</td>
<td>0.94</td>
</tr>
<tr>
<td>r**2</td>
<td>87%</td>
<td>89%</td>
</tr>
<tr>
<td>Constant</td>
<td>92389</td>
<td>90825</td>
</tr>
<tr>
<td>b</td>
<td>-2415</td>
<td>-2553</td>
</tr>
<tr>
<td>c</td>
<td>-----</td>
<td>208</td>
</tr>
<tr>
<td>d</td>
<td>-----</td>
<td>-----</td>
</tr>
<tr>
<td>SEE (rms RE)</td>
<td>2516</td>
<td>2344</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>SEEB</th>
<th>SCOTTISH GAS</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>DWD vs....</td>
<td>TE</td>
</tr>
<tr>
<td>Multiple r</td>
<td>-0.76</td>
<td>0.86</td>
</tr>
<tr>
<td>r**2</td>
<td>58%</td>
<td>74%</td>
</tr>
<tr>
<td>Constant</td>
<td>76050</td>
<td>72665</td>
</tr>
<tr>
<td>b</td>
<td>-1349</td>
<td>-1801</td>
</tr>
<tr>
<td>c</td>
<td>-----</td>
<td>408</td>
</tr>
<tr>
<td>d</td>
<td>-----</td>
<td>-----</td>
</tr>
<tr>
<td>SEE (rms RE)</td>
<td>3169</td>
<td>2490</td>
</tr>
</tbody>
</table>

Already, one is seeing that adding wind after TE improves the strength of correlation (improvement is 95% significant for Scotland), despite the partial regressions of U being trivial. Both gas and electricity behave surprisingly uniformly in this sense. The even more dramatic increase in r**2 (up to 17%) when adding in wind, and the corresponding decrease in SEE are also clear. Here again, we have a curious regional difference, for this does not appear to hold for England. This is possibly due to the greater multicollinearity of TE and U in Scotland. It may also be attributable to the (as yet uncovered) greater sensitivity to wind in Scotland.
At this stage, adding in SRV fails to help matters, except SEEB (Table 6.4); this index is still being swamped by TE and U. Hence we are forced to resort to an alternative technique to evaluate its nature and effects. This will be forthcoming in later Sections.

The slope parameter, \( b \), represents the (average) response rate of demand to TE. For example, SSEB sales rise by about 1349 MWh for every 1 deg C fall (Table 6.4), i.e. about 1.8% of raw demand on average. Likewise, Scottish Gas sendout rises by 86,000 therms/-deg C (2.2% of raw demand on average). These percentages (=100*b/RAW) are much more meaningful than \( b \) for regional comparisons. For SEEB and N.Thames Gas these are 2.8% and 4.1% respectively, again reflecting the greater sensitivity of S.E. England. These figures also show gas sales to be more susceptible to temperature than electricity (in terms of relative proportional % changes), despite lower \( r \) values.

A scatterplot of SSEB deweeked demand vs TE is given in Figure 6.1a. Scatterplots for all four energy data streams are very similar. None of them, including Figure 6.1a, show any evidence of non-linearity in response. That is, there is no visual evidence of demand saturation, down to the lowest temperatures which occurred. Similarly, there is no sign of decreasing sensitivity at higher TE, though no TE in these data approach anything near comfort temperature. Here, then, visual/ graphical evidence is used to complement statistical (linear regression) evidence.

It was hypothesised that some of the dependence of DWD on TE is explained by seasonality (with local trend). The DWD still show high persistence, as confirmed in Section 5.11, which is perhaps due to seasonality. Hence the next desirable step to test this hypothesis is to reduce DWD to stationarity (i.e. deseasonalise, Section 5.12). Removal of the low frequency variability will then permit an assessment of the nature of short-term sensitivity (not induced by seasonality). By "short-term" here we mean "intra-weekly" or "inter-daily". Very encouragingly, almost all sensitivity happens to be inter-daily.
Figure 6.1: a) Scatterplot of SSEB DWD vs TE; b) The stepwise linearly interpolated seasonals (LIN) through SSEB DWD.
6.3. DESEASONALISED DATA

6.3.1. THE INTERPOLATED SEASONALS AND THEIR RESIDUALS

The stepwise linear interpolation scheme ("LIN", Section 5.12) was applied to the DWD and TE records, an example for SSEB DWD is given in Figure 6.1b.

These seasonals explain between 55% and 75% of the variance in the DWD and TE arrays.

6.3.1.1. INTRA-WEEKLY WEATHER SENSITIVITY

The deviations, or residuals, may now be examined for intra-weekly (day-to-day) response to weather. We define DDEV (or TDEV) as deviations of deweeked demand (or raw TE) from stepwise linearly interpolated seasonals. We will not dwell on these residual series here, all being so similar. An example for SSEB and TE is shown in Figure 6.2, with SSEB's residual Acf. If we are to infer the nature of consumer response between days, it is essential that we test the residuals for randomness and establish their degree of coherence, so as to evaluate the results correctly.

Fortunately, most of the persistence has now vanished, as confirmed by SSEB's residual correlogram in Figure 6.2. This is also true of TDEV, though TDEV's Acf is not shown here. There is still some very weak serial correlation residing in DDEV, out to a lag of about 1 day (Figure 6.2). This is meteorologically plausible since short-term demand changes still occur between days after deseasonalisation, e.g. within cold/warm spells.

Since 95% of the Acf falls within the 95% confidence limits for lag r (+/-1.96/√N), and there is no cyclical behaviour or periodicity, we may consider the residual series as the output from a stationary, white noise process.

This desirable condition also holds for all other DDEV and TDEV records. The following multiple cross correlations may therefore be considered as a measure of the linear dependence of the non-autopredictive component of demand on short-term fluctuations.
from LIN, and SSEB's residual correlogram.
Comparison with Table 6.4 tells us that the short-term weather dependence is comparable to the seasonal response, i.e. that for all time scales shown here the response of demand to temperature is similar.

Fortunately, this inter-scale is exactly the time scale on which we will later require demand predictions.

Consistent with Table 6.4, the S.E. shows higher short-term sensitivity, though other inter-regional comparisons are not systematic, and hence are not worthy of comment.

Equally encouraging and important, we are now beginning to see the importance of wind on short-term demand variations. Table 6.5 reveals wind to increase % variance explained by 5-15%, and is particularly marked for Scotland. This indicates greater wind sensitivity in Scotland, despite the relative dominance of the industrial sector there. The importance of SRV is also becoming apparent, particularly for electricity (SEEB shows an 8% increase in r**2), though the improvement is still not statistically significant. Originally, with non-deseasonalised data, the effects exerted by U and SRV were being swamped by TE and
seasonality. Removal of seasonality has provided an initial hint at their importance. There now follows an alternative technique for uncovering their influence.

6.3.1.2. RESIDUAL ERRORS

Multivariate schemes are not always the best way of looking at the effects of supplementary parameters, because such influences may be drowned by more dominating variables. An alternative and productive strategy is to regress residual errors (RE) on U and SRV. We here define RE(1) to be RE when using TDEV alone, i.e. a temperature corrected DDEV; RE(2) when using TDEV and U, i.e. after allowance made (corrected) for TDEV and U, and RE(3) when using TDEV, U and SRV. The number in parentheses, then, refers to the number of model variables:

\[
\begin{align*}
RE(1) &= DDEV - (a + b \times TDEV); \\
RE(2) &= DDEV - (a + b \times TDEV + c \times U); \\
RE(3) &= DDEV - (a + b \times TDEV + c \times U + d \times SRV) \\
\end{align*}
\]

--- (6.1)

Table 6.6 summarises the revealing cross correlations of these RE with U and SRV.

<table>
<thead>
<tr>
<th></th>
<th>RE(1) vs U</th>
<th>RE(2) vs SRV</th>
</tr>
</thead>
<tbody>
<tr>
<td>SEE</td>
<td>0.39</td>
<td>0.52</td>
</tr>
<tr>
<td>NTGAS</td>
<td>0.41</td>
<td>0.13</td>
</tr>
<tr>
<td>SSE</td>
<td>0.51</td>
<td>0.35</td>
</tr>
<tr>
<td>SCGAS</td>
<td>0.45</td>
<td>0.26</td>
</tr>
</tbody>
</table>

All relations in Table 6.6, except \( r = 0.13 \), are significant at 95%. The higher wind sensitivity in Scotland is again showing through, and the importance of SRV, especially for electricity, is once
more coming through. Though not reproduced here, all RE series were found to be near normal and quasi stationary.
Table 6.6 could have been arrived at from Table 6.5, indirectly by various steps, though the reasons for the small inconsistency (apparent discrepancy) of statistical significance between the 2 tables are not clear. As supplementary evidence, the following technique will look at the influences of U and SRV from a rather different angle.

6.3.1.3. WIND AND MISERY CORRECTION FACTORS

To return to multivariates, the relative magnitudes of b and c (TDEV and U slope parameters) tell us something about winds relative importance to TDEV. The b parameter has units (for electricity) MWh/deg C and the units of c are MWh/knot. Division of b by c will yield a quantity with dimensions knots/deg C. This provides us with a very useful measure of how many knots have the equivalent effect on demand as 1 deg C (and its sign). Table 6.7 gives these “wind correction factors” (WCF= b/c), as we shall term them, together with those for SRV (explained soon).

Table 6.7: Wind Correction Factors (WCF = b/c) and Misery Correction Factors (MCF = b/d), i.e. temperature equivalents of U and SRV

<table>
<thead>
<tr>
<th></th>
<th>WCF (knots/deg C)</th>
<th>MCF (SRV units/deg C)</th>
</tr>
</thead>
<tbody>
<tr>
<td>SEEB</td>
<td>+12.9</td>
<td>+66</td>
</tr>
<tr>
<td>NTAS</td>
<td>12.8</td>
<td>271</td>
</tr>
<tr>
<td>SSEB</td>
<td>6.4</td>
<td>41</td>
</tr>
<tr>
<td>SCGAS</td>
<td>8.2</td>
<td>60</td>
</tr>
</tbody>
</table>

Those WCF’s derived here (of the order of 10 knots/-1 deg C) are of comparable magnitude to 18 knots = -1 deg C used by W. Midlands and Eastern Gas Boards to wind-correct their temperatures (though derived there by other methods). This was discussed in Section 5.9.2.4. in relation to “equivalent temperatures”. The wind correction factors are somewhat higher for England. This could be a subtle
manifestation of the different multicollinearity between regions or, more likely, the greater wind dependence in Scotland (Table 6.5).

By uncovering the relation in this indirect way, we can now more confidently believe higher windspeeds to increase demand (Table 6.7), despite the apparently trivial (and -ve) regressions of U on DWD (Table 6.3).

In a directly analogous way, similar "misery correction factors" (MCF) can be derived for SRV (MCF = b/d). How many SRV units (remembering SRV is dimensionless) are equivalent to 1 deg C on energy usage? These too are shown in Table 6.7. The relative insensitivity of NTGAS to misery is again in evidence.

Both results (WCF and MCF) are of considerable interest in assessing the relative importance of meteorological factors. For instance, the whole possible range of SRV values (=100) can only contribute the equivalent of about 2 deg C on demand at the very most, as Table 6.7 depicts. Since the range of mean daily U is from 0 to 24 knots, this contribution for wind increases to more than 3 deg C for Scotland, 2 deg C for England (Table 6.7).

### 6.3.2. THE AUTOPROJECTED SEASONALS AND THEIR RESIDUALS

The autoprojected seasonal factors ("PROJ") are all very similar, those for Scottish Gas are reproduced in Figure 6.3a. The autopredictions follow basically the same level of seasonality and local trend as stepwise interpolations (Figure 6.1b). One thing to notice is that the scheme does have a slight tendency to overshoot in its representation of seasonality. It lags behind week to week changes slightly, i.e. it never quite manages to catch up with seasonality, e.g. around Day 50 in Figure 6.3a. We need not worry, since this slight lag is introduced into both DWD and TE. The deviations will therefore be equally affected, this has the effect of slightly exaggerating their interdependence. We will hereafter refer to DDEV (or TDEV) as deviations of deweeked demand (or raw TE) from autopredicted seasonals (PROJ), or alternatively residuals.

Hence the residuals behave slightly differently from

---

* being an asymmetric filter.
Figure 6.3: a) The autoprojected seasonals (PROJ), fitted to SCGAS deweeked demand; b) Deviations of SCGAS DWD from PROJ (DDEV) for days 1..49; c) DDEV ACF and probability distribution.
those for LIN. This is another reason (see Section 5.14) why we have to backcast autoprojections for the first half (to model deviations from them), and not use LIN for the first half. This also ensures statistical consistency, though there is little difference in forecast accuracy either way.

Figure 6.3 also gives the deviations from PROJ (for the first 49 days only, since model coefficients to predict the second half will be derived from these only). It was a requirement of cross correlating residuals that they be normally distributed and close to stationarity (stochastic random records). Figure 6.3 gives the % frequency (probability) distribution of SCGAS DDEV (as an example), showing approximate normality. The residual correlogram in Figure 6.3 indicates weak serial correlation and no periodicity, hence the series is almost stochastic white noise. All other DDEV and TDEV records were found to be near normal and pseudo-random.

6.3.2.1. INTRA-WEEKLY RESPONSE TO WEATHER

A stepwise multiple regression of the residuals (for the first 49 days) now follows, and it is coefficients obtained here that will be used to make forecasts for the second half.

Table 6.8: Multiple regression analysis of the residual (deweeked and deseasonalised) records for the first half (days 1-49). DDEV, TDEV are deviations of DWD and TE from autoprojected seasonals.

<table>
<thead>
<tr>
<th>DDEV vs...</th>
<th>TDEV</th>
<th>TDEV+U</th>
<th>TDEV+U+SRV</th>
</tr>
</thead>
<tbody>
<tr>
<td>SEEB</td>
<td>r</td>
<td>-0.84</td>
<td>0.88</td>
</tr>
<tr>
<td></td>
<td>r**2</td>
<td>71%</td>
<td>77%</td>
</tr>
<tr>
<td>NTGAS</td>
<td>r</td>
<td>-0.88</td>
<td>0.90</td>
</tr>
<tr>
<td></td>
<td>r**2</td>
<td>78%</td>
<td>82%</td>
</tr>
<tr>
<td>SSEB</td>
<td>r</td>
<td>-0.68</td>
<td>0.83</td>
</tr>
<tr>
<td></td>
<td>r**2</td>
<td>46%</td>
<td>69%</td>
</tr>
<tr>
<td>SCGAS</td>
<td>r</td>
<td>-0.74</td>
<td>0.88</td>
</tr>
<tr>
<td></td>
<td>r**2</td>
<td>54%</td>
<td>78%</td>
</tr>
</tbody>
</table>
Once again, the weather dependence on both the intra-weekly and the seasonal time scale is comparable (compare Tables 6.8 and 6.4). The improvement when adding $U$ is much more pronounced for Scotland (actually in excess of 23% in $r^2$), and is significant at 95% for SCGAS, 90% for SSEB. The greater wind susceptibility in Scotland is yet again manifesting itself.

Adding SRV improves things slightly, though Table 6.6 has already pointed to its importance. Later, too, SRV will be shown to be rather fundamental. Here, TE and $U$ are now dominating the multiple correlation coefficient.

### 6.3.2.2. RESIDUAL ERRORS

The residual errors when using only TDEV, i.e. $RE(1)$, will shortly be cross correlated with various formulations of CPW. It is here, therefore, that they need to be most thoroughly tested for periodicity, serial correlation, normality and non-linearity. It is important that we do this anyway. All residual records were put through spectral and superposed epoch routines, autocorrelations, normality tests and scatterplots for these respective purposes. All $RE$ series were found to be near normal and quasi-stationary. Figures 6.4 and 6.5 present example graphical output from these tests, for SSEB.

If we concentrate firstly on Figure 6.4, the $RE(1)$ series (first 49 days, of course) is given with its correlogram and probability distribution. The record is almost normal and is pseudo-random, only very feeble serial correlation out to about 1 day residing in it. Beyond this, the Acf rapidly dampens. Slightly more than 5% of the Acf falls outside the 95% confidence bands of $\pm 1.96/\sqrt{N}$, but the relatively large value at lag 4 could be an artefact of the response of the autoproduction filter process, but is not considered important in evaluating cross correlations between residuals.

We would hope for no periodicity in these traces too, and the Acf in Figure 6.4 confirms the absence of any
Figure 6.4: 

a) The RE(1) trace for SEEB; 

b) The correlogram of SEEB RE(1); 

c) Probability distribution of SEEB RE(1).
Figure 6.5: a) Superposed epoch analysis of SEEB RE(1); b) Harmonic spectrum for SEEB RE(1).
significant oscillatory behaviour. For these applications, it becomes particularly desirable to confirm that no 7-day cyclical behaviour is left in DDEV and hence RE(1), due to the efficiency (or otherwise) of the weekly adjustment scheme. We have already demonstrated the scheme to be satisfactory when using non-desesasonalised demand. Now we are working with residual errors, subtle indirect effects of the technique can feed through and be revealed by these tests. In particular, any remaining 7-day periodicity will be very sensitive to harmonic and superposed epoch analysis.

Moving now to Figure 6.5, therefore, here we show univariate superposed epoch and Fourier analyses of the same SEEB RE(1) series. Superposed epoch analysis testifies that there is no systematic weekly pattern in the day of week means, except perhaps marginally lower weekend means. This could possibly result from the weekly cycle in b. This fails to show up in superposed epoch analysis of the DDEV or in the Acf, and is insignificant. As additional confirmation, the harmonic spectrum in Figure 6.5 exhibits no proponderance of wave 7 (representing weeklies in these 49 day series), and no periodicity at any other frequency.

All RE traces were found, in these ways, to be free from cycles, skewness and coherence. In addition, they were tested for non-linearity at each stage by scatterplots. Though these results will not always be presented, all were found to be linear. Hence we can now use these RE(1) records for each energy array to construct CPW.

6.4. THE WINDCHILL FIELDS

The residual errors when using TDEV, i.e. temperature corrected DDEV (see equation 6.1) for the first half, may now be cross correlated with various TCOMF and k in CPW (equation 5.10), as detailed in Section 5.13, see also equation (5.19). This empirical maximisation approach will allow us to select an optimal formulation for CPW. We would naturally expect high underestimates of demand (+ve RE) to go hand in hand with high CPW, not only on extremes but also on average. Having empirically decided on an optimal windchill parameterisation (i.e. chosen values of TCOMF and

* The large amplitudes of waves 4 and 6 could arise from the autoprojection scheme.
k), and proven it to be superior to U, we can predict the second half.

As regards the choice of k, whilst we are testing the accepted values of 0.5, 1.0 and 2.0, it is important to remember that the response of a regional aggregate of customers will be a complex amalgam or conglomerate of different physical laws (k values, Section 5.9.2), e.g. those applying to convective/ conductive heat loss from bodies, buildings, etc. Because of this mixture, it follows that k values between 0.5, 1.0 and 2.0 could well be physically reasonable, though we will, for consistency and to accord with the literature, select one of these accepted values.

6.4.1  2-d CONTOUR AND 3-d BLOCK CORRELATION DOMAINS

The first example windchill field, for SCGAS, is presented in Figure 6.6. This gives a 2-dimensional contour plot and a 3-dimensional perspective histogram of the correlation field of RE(1) vs CPW, for various combinations of TCOMF and k. Note that in both representations the k=0.0 plane is included twice. The vertical scale represents the cross correlation coefficient, r, between RE(1) and CPW. Looking more closely, the shaded area in the contour plot is the region of highest correlation (r=0.75), within which r does not vary significantly. Correlations as high as 0.75 of CPW with RE(1) surely testify to the need to incorporate CPW. Correlations of RE(1) with no wind (i.e. just TCOMF-TA in equation 5.10), are clearly zero, but rise very sharply as we add wind, up onto the broad ridge shaded. Once onto this plateau, they fall off more gradually as the wind exponent (k) is increased even more.

The 3-dimensional histogram provides a much more realistic and useful visualisation of the correlation domain, with perspective and hidden lines to produce correct visibility. The cliff shows the initial rapid improvement when increasing the wind exponent, and the steps along it tell us which TCOMF to choose, should we decide on a low k value. The broad ridge is apparent. The gently sloping plateau falls away gradually as we increase TCOMF and k.
Figure 6.6: 2-d contour plot and 3-d histogram of the windchill correlation domain for SCGAS: RE(1) vs CPW for various TCOMF and k.
Such visual confirmation to complement the statistics is extremely useful in making the choice, remembering here that we are really testing the accepted values of TCOMF=18 deg C and k=0.5 or k=1.0. There are certain interpretation problems and some difficulties arising from subjectivity, as these fields have all sorts of subtleties embedded in them. For example, though RE are very sensitive to k (at least for k<1.0), they are relatively insensitive to TCOMF (Figure 6.6). This is because U dominates the correlation with RE (shown later). Changing TCOMF, therefore, has a comparatively small effect on the outcome of the correlation. Another possible explanation is that no temperatures in these data sets approach anywhere near TCOMF=18 deg C. Mean daily TA never managed to rise above 9.8 deg C in Scotland during this severe winter (11.9 in England). This explains why the shaded area does not close off at high TCOMF. Similarly, increasing the wind exponent above about k=0.5 has little effect other than worsening the correlation, though it is not obvious why the worsening is so gradual (Figure 6.6).

The ringed grid point and the shaded square is the point chosen for our CPW: TCOMF=18 deg C and k=0.5, for the above reasoning. That is, the accepted values are supported here. Though the choice of k is statistically and visually justified, that of TCOMF is to some extent more arbitrary. Our diagram does support the accepted value of TCOMF=18 deg C, however, and so our choice is consistent with the literature and physics. The assumption that wind has no cooling power above 18 deg C is sensible, since experience has shown that 18 deg C is generally acceptable as comfortable for normal domestic life patterns in the U.K. Exceptions do occur, e.g. operating theatres in hospitals need to be maintained at 26.7 deg C, and the statutory limit for frost protection is to keep interior temperatures above 4.4 deg C. The average of 18 deg C is widely accepted as comfortable.

It is worth bearing in mind that an extra 2 or 3 deg C (18 vs 21 deg C for TCOMF) arises from other sources besides heating. These include people, cooking appliances, lights
and passive solar radiation (interception of sunshine through windows). That is to say, not all of the heating requirements of a building are supplied by its heating plant. These passive energy gains are known variously as "free heat gains" by Leach (1981), "fortuitous gains" by BRE (1975) and "internal gains" elsewhere. To illustrate the importance of people on free heat gains, it is interesting and surprising to note the following. In a perfectly insulated house (zero thermal conductivity) with necessarily zero air changes, then purely from body heat given off to the environment, one would die of heat before lack of oxygen.

The values of $k=0.5$ and $\text{TCOMF}=18$ deg C selected (confirmed) here are not only relatively common ones in the literature, but are also physically supported. The $k=0.5$ choice implies that buildings behave rather like people in their heat loss (Section 5.9.2.3), though we could have selected inbetween values of $k$, as explained earlier. The values of $k=1.0$ and 2.0 were not supported here, and both produced slightly worse forecasts.

The remaining correlation fields for the other energy data arrays are encouragingly all very similar. Figure 6.7 presents 2-d contour plots for SSEB and NTGAS. The corresponding 3-dimensional histogram for SSEB is also presented, this time viewed from a slightly different elevation angle and azimuth. $\text{TCOMF}=18$ deg C and $k=0.5$ are once again supported graphically and statistically, for the same reasons as Figure 6.6. The ringed grid point and arrow (at point A) represent these. For SSEB, the 3-d block diagram again shows the cliff between $k=0.1$ and $k=0.4$ and the ridge of highest correlation ($r>0.70$) along $k=0.4/k=0.5$. The plateau slopes gently away thereafter, though rather more steeply at first, which strengthens our decision for $k$.

It is indeed remarkable that the same laws manifest themselves in these domains, both between regions and fuels. Further substantiation by examination of other data sets would still be desirable.

For N. Thames Gas, the superiority of $k=0.5$ is not so
Figure 6.7: Contour plots of the CPW correlation field for SSEB and NTGAS, and SSEB's corresponding 3-d perspective surface.
well defined (Figure 6.7), though clearly TCOMF=18 deg C is valid. Since we are simultaneously testing k=1.0 and 2.0 (both physically sensible) then we must consider the feasibility of selecting these. In the NTGAS domain, k=0.5 and k=1.0 fall on the same broad plateau of highest correlation (Figure 6.7). The k values of 1.0 and 2.0 produced marginally worse forecasts (see later) and k=0.5 was therefore retained.

Figure 6.8 for SEEB, in contrast, shows clearly that this time k=1.0 is visually more reasonable on both contour and perspective plots. The area of maximum cross correlation is closer to k=1.0 here. In this case, k=0.5 and 2.0 yielded slightly worse forecasts, and we are forced to choose k=1.0. TCOMF=18 deg C is still reasonable, hence this example of our decision process represents a compromise between our statistical/graphical evidence and the literature/physics. It also brings out an interesting inter-regional comparison, and a difference between fuels, though possible physical explanations are far from obvious.

For all cases, graphical/visual evidence has been used to complement statistical evidence, so as to empirically determine CPW. The resolution of the correlation domains reflects a compromise between a fine and coarse mesh grid, and was actually obtained by contracting a much coarser grid size originally intended to identify general changes in sensitivity over the domain. Hence continuation of the fields shown, at their extremeties beyond the domain boundaries, would not be productive.

The same general pattern in the correlation domain has emerged, both between regions and fuels, for totally different energy data sets. This regional similarity is not only rewarding in itself, but it points to the applicability of the technique to other data sets.

6.4.2 RESIDUAL ERRORS, WINDCHILL AMD MISERY

Hereafter, the CPW statistic will replace U. To be totally unbiased, what we should really do to justify replacing U by CPW is to compare the correlations of U and CPW with RE(1). Table 6.9 summarises these results and
S.E.E.B. CPW FIELD

WINDCHILL CORRELATION FIELD FOR S.E.E.B

azimuth = 120
width = 3.00
height = 1.50

Figure 6.8: 2-d and 3-d representations of the windchill correlation domains for SEE.B.
demonstrates how the strength of regression improves due to CPW. The Table also includes cross correlations of RE(2) with SRV. RE(2) is now defined as RE using TDEV and CPW, as in equation (6.1) but using CPW instead of U. Hence RE(2) now represents DDEV corrected for TE and CPW.

Table 6.9: Cross correlations of residual errors (using deviations from autopredicted seasonals) with U, CPW and SRV, for the first half (49 days); RE(1) is using TDEV, RE(2) from TDEV and CPW

<table>
<thead>
<tr>
<th>RE(1) vs.</th>
<th>U</th>
<th>CPW</th>
<th>RE(2) vs. SRV</th>
</tr>
</thead>
<tbody>
<tr>
<td>SSEB</td>
<td>r</td>
<td>0.55</td>
<td>0.68</td>
</tr>
<tr>
<td></td>
<td>r**2</td>
<td>30%</td>
<td>46%</td>
</tr>
<tr>
<td>SCGAS</td>
<td>r</td>
<td>0.60</td>
<td>0.75</td>
</tr>
<tr>
<td></td>
<td>r**2</td>
<td>36%</td>
<td>56%</td>
</tr>
<tr>
<td>SSEB</td>
<td>r</td>
<td>0.44</td>
<td>0.39</td>
</tr>
<tr>
<td></td>
<td>r**2</td>
<td>19%</td>
<td>15%</td>
</tr>
<tr>
<td>NTGAS</td>
<td>r</td>
<td>0.41</td>
<td>0.43</td>
</tr>
<tr>
<td></td>
<td>r**2</td>
<td>17%</td>
<td>19%</td>
</tr>
</tbody>
</table>

Scotland's susceptibility to windchill (even more so than to U) is readily apparent. The somewhat lesser sensitivity of London and S.E. England is reflected here, in that windchill only offers a marginal improvement over U, and a slight (though not significant) worsening for SSEB. On extreme occasions, however, we will show the explicit need for CPW for SSEB, and to retain it for general use for SSEB does not lower forecast accuracy, as we shall see. CPW improves forecast accuracy substantially for the other three data streams. For Scotland, substituting CPW for U explains an additional 15-20% of the variance in RE(1), and all regressions of CPW with RE(1) in Table 6.9 are highly significant in themselves (at >99%). Wind was initially swamped by TE, but its explicit functional combination with TA has uncovered a highly significant effect, via its interaction with temperature as windchill.

Table 6.9 does in fact contain a lot of other
information in condensed form. It shows how strongly RE(2), now from TDEV and CPW, depends on SRV (for electricity). This is significant at 95% for SEEB, 90% for SSEB. Incidentally, this is higher than SRV vs RE(2) from TDEV and U, in all cases.

For gas, this dependence is poor, suggesting at first thought that perhaps SRV could be dropped for gas. Later we will give conclusive evidence that it most definitely should not, especially in extreme misery situations.

6.4.3. STATISTICAL PROPERTIES OF THE CPW STATISTIC

Now that we have chosen CPW, and replaced U by it for the forthcoming demand forecasts, it is obviously important to be aware of CPW's statistical characteristics (distribution, persistence, etc). For all data sets except SEEB, CPW is now given by \( U^{0.5} \) (18-TA). For SEEB it becomes \( U^{1.1} (18-TA) \). We will concentrate on the properties of the former definition, though both are very similar.

Figure 6.9 gives the CPW record itself, whose peaks show a remarkable correspondence with raw demand maxima in Figures 5.2 and 5.3. One would expect high windchill days to go hand in hand with high energy consumption, for the many reasons given in Section 5.9.2. and elsewhere. Though not reproduced here, and despite such coincidence of peaks, the regressions of CPW on demand were considerably weaker (of the order of \( r=0.40 \)) than with TE. The many arguments, this amongst them, for not replacing TE by CPW, and for adding it stepwise after TE, were advanced in Section 5.9.2.

Figure 6.9 also provides the correlogram of windchill and its probability distribution. CPW is found to possess some short-term serial correlation (2-3 days), naturally enough being a combination of U and TA. Hence on average, high windchill situations tend to follow high windchill situations in groups of 2-3 days, e.g. cold windy periods. CPW is slightly negatively skewed, due to the sharp cut-off or limitation at \( U=0 \) knots (negative CPW was made impossible), but this skewness is not marked.

The units of CPW are knots**.deg C, hereafter simply referred to as CPW units for brevity. For graphical
Figure 6.7: Statistical properties of CPW:

- The CPW record for 90 days;
- CPW's correlogram;
- Distribution.
6.4.4 WINDCHILL CORRECTION FACTORS

If we were to go back and repeat all the previous multivariate analyses using CPW instead of $U$, we would find an improvement, though these are not given here. Furthermore, if we were to use the technique derived in Section 6.3.1.3. for calculating wind correction factors, we could similarly arrive at "windchill correction factors" in a directly analogous way. These would tell us how many windchill units (knots**k.deg C) would be needed to have the equivalent affect on demand as 1 deg C. They are given by $b/c$, where $b$ and $c$ are the respective multivariate slope parameters of $DDEV$ vs $TDEV$ and CPW.

For Scotland (SSEB and SCGAS), such windchill correction factors are 15 CPW units/—deg C (where CPW range is 20-89). For NTGAS (with similar CPW range as Scotland) the windchill correction factors are 160 CPW units/—deg C. This shows the relative insensitivity of NTGAS to windchill. For SEEB (having a different CPW formulation and a range of 14-395) such factors are also about 160 CPW units/—deg C.

Comparison of the ranges with these windchill correction factors tells us that for Scotland windchill can exert the same effect on energy demand as 4 deg C over the whole possible CPW range, NTGAS 0.5 deg C, SEEB about 2 deg C. This again serves to confirm the greater susceptibility of Scotland to windchill, and its importance generally.
6.4.5. A CPW NOMOGRAM

It is of particular interest in some applications of windchill, including this one, to manually read off values of cooling power for different temperatures and windspeeds. A diagram has been specially constructed here for this purpose. Such a "nomogram" gives the windchill as a function of TA and U. Figure 6.10 presents such a convenient graphical representation, in both 2 and 3 dimensions. From the contour plot one can read off values of cooling power from given values of TA and U. The field is also plotted as a 3-dimensional surface (perspective drawing) for better visual realisation of the domain.

CPW is at a maximum at very low TA and high U. Our windchill is clearly zero when T>TCOMF, by definition, since wind has no cooling power when we are comfortable. We can use heating to bring interior temperatures up to TCOMF, but when T exceeds TCOMF there is nothing we can do to lower T. This is assuming negligible space cooling/air conditioning load, which is reasonable for daily data, though there is a weather-insensitive air conditioning base load in shops and factories. Certainly in these data arrays, TA never even approaches TCOMF (18 deg C). Hence the assumption of negligible space cooling load (fans, forced ventilation) in this country is justified. Baker (1977) demonstrates that there is no identifiable existence of air conditioning load at present in Britain on a daily basis. He was looking at daily electricity demand on the CEGB during the drought of summer 1976. Elsewhere, e.g. in hot climates, one could conceivably have a negative windchill (by allowing CPW to go -ve when T>TCOMF), which would be counteracted by the forced use of air conditioning, refrigeration and space cooling.

For us, CPW vanishes when TA gets above 18 deg C. Clearly, we are also forced to curtail CPW to zero when U=0.

This windchill concept is very useful for understanding consumer reactions, since how individuals perceive T is influenced by windiness and hence body (and by analogy buildings) heat loss, as discussed at length in Section 5.9.2. Some windchill literature was referred to in Chapter 5, and it is normally quoted in cal/m^2h or
NOMOGRAM OF CPW

\[ \text{NOMOGRAM OF CPW} = U \times K \times (T_{\text{COMF}} - T_{\text{A}}) \ldots \text{WINDCHILL FIELD} \]

\[ \text{azimuth} = 170 \quad \text{altitude} = 15 \]
\[ \text{width} = 4.00 \quad \text{height} = 2.00 \]

Figure 6.10: 2-d and 3-d nomograms of windchill
W/m² in mountain weather applications. For instance, Siple and Passel (1945) define windchill (H) empirically by:

\[
H = (10.45 + 10 \sqrt{V} - V) \times (33 - T) \tag{6.2}
\]

where: \( V \) is windspeed in knots, \( T \) is temperature in deg C and \( H \) (windchill) has units kcal \( \text{m}^2 \text{hr}^{-1} \).

If we could establish a physical or empirical relation between our CPW (knots*deg C) and body/ building heat loss (in W/m²), then diagrams such as Figure 6.10 would have important practical applications and theoretical repercussions. This is because CPW is related to the rate of body cooling (people or buildings alike), ventilation rate and air changes, and therefore to heating requirement. Similar nomograms could therefore be constructed for these factors and used in an operational context to read off appropriate values of fuel requirements.

6.5. SYNOPTIC SITUATION AND RESIDUAL ERRORS

6.5.1. THE MARRIAGE OF SYNOPTICS WITH STATISTICS

We have observed how well residual errors, when using only TDEV, correlate with CPW (e.g. \( r > 0.75 \)), and we have chosen CPW from these RE. We have also seen how, as a consequence, including windchill introduces a positive improvement in terms of \% variance in DDEV explained. Other types of evidence were also used to complement the statistics, such as visual (scatterplots) and various graphical representations of CPW’s properties (correlogram, frequency distribution). It is clear now that on average we should incorporate windchill. Though the statistical evidence for SRV was not as strong, it was shown to be significant in several ways, and it too must be retained as a working model parameter, as we will show.

We now move on to a completely different but very important kind of visual evidence, that of synoptic/ mesoscale weather situation. This again will support the statistics, and will make clear the need to explicitly
include CPW especially on extreme occasions, but also in
general. We will examine in detail some interesting extreme
and sudden synoptic situations where inclusion of CPW and
SRV would be vital to a good demand forecast. These are
simultaneously occasions of model failure when using only
temperature. After presenting the synoptic evidence to
finally confirm the need of CPW and SRV, we can then move on
to the final demand forecasts. See Atkinson (1981) and
McIntosh and Thom (1973) for mesoscale and synoptic
meteorology respectively.

It is here where one can run into various
philosophical difficulties. What exactly does one show to
demonstrate the necessity of these supplementary indices?
One can always pick out extremes that go hand in hand with
residual errors. On the contrary, one can pursue the
statistical approach and cross correlate RE with CPW and SRV
(as we have done). The approach adopted here avoids this
apparent dichotomy, and represents a compromise in that
particular synoptic situations are selected objectively, and
used to complement or calibrate the statistics, and not to
replace them. Statistics and synoptics should not really be
divorced, as they normally are, but rather should be married
together, so as to demonstrate the systematic dependence of
RE on CPW and SRV via synoptic/ mesoscale pattern.

6.5.2. RESIDUAL ERRORS AND SYNOPTIC SELECTION CRITERIA

To pursue this, let us investigate the dependence of
RE(1) on CPW, and RE(2) on SRV, as we have already done in a
statistical sense. The RE(1) and RE(2) traces for SSEB are
given in Figure 6.11. These RE are those using deviations
from stepwise interpolated seasonals, as this provides a
particularly clear illustration of the forthcoming
arguments. Also, this is a full length (90-day) record,
which will be especially useful in the following discussion
of synoptic pattern. The use of a 90-day stretch would be
impossible using RE derived from deviations from
autoprojected seasonals, i.e only 49 days. The arguments are
completely general, however, and apply to both cases.

Since we will be looking at synoptic pattern and RE in

* The same 90-day period was used in the formulation of CPW
and SRV.
Figure 6.11: Residual errors, CPW and SRV for SSEB, for comparison with synoptic situations in Figures 6.13, 6.14 and 6.15, to which the alphabetical annotation refers.
Figure 6.12: Residual errors and CPW for SCGAS. For comparison with synoptic situations in Figures 6.13, 6.14 and 6.15.
relation to CPW and SRV, these latter two series are shown above RE in Figure 6.11 on the same diagram. Vertical lines for each selected synoptic situation have been drawn across these coincident series to facilitate cross reference. Such traces for SEEB are very similar, and will not be presented here. The reader will also find these series for SCAS in Figure 6.12, but should note that this time we do not show SRV or RE(2). This is because the dependence of RE(2) on Misery is less strong for gas, as we have seen. The corresponding traces for NTGAS are so similar to SCGAS as to warrant their omission. It is rather difficult to display superimposed series in monochrome, and on occasions the feint traces in these Figures cannot easily be distinguished from the darker line. In most cases, careful inspection will clarify the points.

Closer examination of Figure 6.11 reveals RE to lessen after adding CPW (generally, but not always), as one would hope. We have already proven this in a statistical sense. Similarly, incorporation of SRV often lessens RE. Thus Figure 6.11 shows the successive improvements as allowance is taken of CPW and SRV. Though most of the peaks and troughs are explicable in terms of weather patterns, we will examine just a few of the extreme and sudden of such events. The arguments do hold generally, as the statistics showed. High positive RE(1) should coincide with high windchill, and high positive RE(2) with high misery. A closer investigation of several events substantially confirms this expectation.

Firstly, we need to establish objective criteria for how the synoptic situations are chosen. The selection procedure was as follows. For SSEB (Figure 6.11), the five highest RE(1) spikes/troughs (absolute magnitude) were chosen for comparison with synoptic pattern, all of whose absolute value lies >2 standard deviations from the mean absolute RE(1). Additionally, two more interesting (what the author thought to be interesting) sudden synoptic predicaments were picked out rather more arbitrarily, but which do nevertheless correspond to peaks or troughs on the RE traces. For consistency, the same seven days were chosen for comparison with gas RE, and coincided closely with the
peaks therein. The last spike, at day 88, will be dealt with later.

The final seven synoptic situations, (annotated A to G on Figures 6.11 and 6.12), are thus a mixture of objective and subjective selection criteria, but which are also a compromise for all four data sets. As such, even though SEEB and NTCAS are not given here, the relations of RE with synoptic pattern are basically very similar to SSEB and SCGAS. Most of the comments to follow, therefore, apply to all energy data streams.

The weather patterns to be displayed should be referred to in conjunction with the RE traces in Figures 6.11 and 6.12. The reader may also find it instructive and useful to refer back to the raw meteorological plots given in this Chapter and the last for additional confirmation of the reasoning. Numerical figures of meteorological variables quoted apply just to Scotland for brevity, but the reasoning applies equally to London and the S.E. There is, in fact, a remarkable uniformity in the regional variation of response.

6.5.3. SOME EXTREME AND SUDDEN SYNOPTIC/MESOSCALE EVENTS

Figure 6.13 shows three very interesting and extreme synoptic predicaments. These correspond to peaks A, B and C on Figures 6.11 and 6.12. The relevant sections of the RE traces are tabulated numerically on Figure 6.13 (and later Figures) for reference. The example used in these tables is SSEB, and the extreme days looked at here are indicated thereon by being boxed.

Firstly, perhaps the most interesting and certainly the most severe situation of the whole winter is given in Figure 6.13 (A), peak A on Figures 6.11 and 6.12. This is Feb 15 (Day 46), the famous day within the power industries already referred to, having such a massive windchill. Large underestimates of demand occurred on this occasion, since no chill factor was included in their models at that time (and still isn’t for SSEB). There was a blocking high over Scandinavia, maintaining a bitterly cold ENE airstream over all of Britain. The flow is strong over Central Scotland and even stronger over London and the S.E. This, coupled with
Figure 6.13: Three extreme synoptic situations, high windchill, high misery and low windchill situations (compare Figures 6.11 and 6.12); with corresponding section of RE trace (in MWh), CPW and SRV.
temperatures around -4 deg C combined to produce the second highest windchill of the entire winter (CPW=81). The highest CPW of 89 occurred the previous day, and like this day corresponds to high positive RE(1). The easterly flow is very unstable, with frequent and heavy instability snow showers along the East coast. Had windchill been included, then such catastrophic model failures might never have happened. This is evidenced by the reduction of RE on incorporation of CPW for both gas and electricity.

Moving now to a high misery situation (Feb 21, Day 52). Figure 6.13 (B) and peak B on Figures 6.11 and 6.12. The latter Figures show RE to actually worsen on inclusion of CPW. SRV is responsible for this. This day was one of the highest SRV's of the winter (SRV=74). An almost stationary cold front lay N-S across the U.K. Sunshine hours were zero, very poor visibility and seven hours of rain combined to produce very high misery. RE(3) is better than RE(2), but RE(3) is still worse than RE(1), which is somewhat disturbing. We must, of course, show the failures as well as the successes. This possibly suggests we should derive coefficients for SRV (d*SRV in equation 5.22) from only extreme days and not the whole data set. This will be debated later. Though we cannot always succeed, all the illustrations to follow (and the first one) are examples of positive improvement.

The next situation, Figure 6.13 (C) and trough C on Figures 6.11 and 6.12, is three days later (Feb 24, Day 55). This was a very pleasant day of low windchill, and at the chart time one of low misery. A mobile anticyclone had become temporarily established over the British Isles. Over Scotland, there was very little or no wind (CPW=20), 4.5 hours of sunshine, good visibility and zero rainfall. Inclusion of CPW reduces RE substantially for gas and electricity.

Next, we will detail a low misery situation, Figure 6.14 (D), Jan 16, trough D in Figures 6.11 and 6.12. This day corresponds to a very large negative RE(1). That is, large overestimates of demand were made using temperature alone. Building in CPW made little improvement. This can be
Figure 6.14: Two opposing synoptic patterns: low windchill and misery, and high windchill situations (compare Figures 6.11 and 6.12). RE(1) from using TDEV only, RE(2) from TDEV and CPW, RE(3) from TDEV, CPW, and SRV.
explained by very low misery (SRV=23). Scotland was immersed in cold, clear anticyclonic northerlies behind a weak cold front, with four hours of sunshine and excellent visibility (the highest of the winter: a remarkable 58.9 km). On incorporation of SRV, RE reduces considerably.

Let us now move on four days later, Jan 20, situation E in Figure 6.14, spike E on Figures 6.11 and 6.12. In complete contrast here we have very large positive RE(1), due to one of the highest windchill days of the three months. Scotland was covered with a cold wet ENE flow, with sleet and snow over Glasgow and Edinburgh and 30 knot mean winds (CPW=66). Even after taking CPW into the model, demands were underestimated (large RE(2)), though RE does reduce. Once more, we are witnessing the effect of high misery (SRV=78), resulting from total cloud cover and hence zero sunshine, poor visibility and nearly 11 hours of precipitation (mostly frozen). RE is again observed to decrease for both fuels.

Finally, a somewhat later section (early March) of the RE records will now be looked into. The first 10 days of March saw Britain in a progressive westerly synoptic regime. This is a situation where accurate timing of mobile troughs and ridges, cold fronts and warm sectors, is important. The section of the RE traces around F and G in Figures 6.11 and 6.12 exhibits continual large amplitude variations (in magnitude and sign) of RE. This came about as a result of sudden changes due to rapidly travelling synoptic scale disturbances and frontal systems.

For example, situation F in Figure 6.15, trough F on Figures 6.11 and 6.12, corresponds to Day 61 (March 2), and is in the midst of the zonal westerly spell. On this day the U.K became quite quickly immersed in a strong mild SW airstream carried by a brief swiftly moving warm sector. Despite TA exceeding 10 deg C, and windchill being low (CPW=38), misery was well up (SRV=70). There was almost no sunshine, poor visibility and 7 hours of rain (typically Tropical Maritime flow). Inclusion of CPW slightly increases RE but using SRV lowers it again (for electricity). Sudden warm fronts and vigorous wet, windy and miserable warm
Figure 6.15: Sudden warm sector (high misery) and sudden cold front (high windchill). Tabulated RE in MWh. Compare with Figures 6.11 and 6.12.
sectors also occur elsewhere in the period.

A totally opposite pattern is depicted in Figure 6.15 (C), spike G in Figures 6.11 and 6.12. This peak on Day 68 (March 9) reflects a sudden cold front sweeping down across the country. This rather quickly covered the whole of Britain in a very cold, blustery and showery unstable Polar Maritime airstream from the N.W. (CPW=67). The occasion is memorable by the sudden onset of blizzards and severe drifting. This resulted in a sudden overloading of the power supply systems. Yet again, residual errors reduce considerably when using windchill, for both fuels.

The above examples were chosen as illustrative objectively (largest RE(1)), but other peaks and troughs could have been selected using different criteria. For example, had we chosen the largest CPW or SRV, then we would too have found close correspondence with RE. The period is full of interesting examples of this dependence, e.g. other Easterly blizzards and short blocking spells, sudden and extreme frontal passages, etc. Similarly, we could have attempted some empirical classification of RE by synoptic type, or to categorise RE by airmass type.

We cannot always succeed, however, and there will always be exceptional occasions which cannot be explained. One such example is the last spike on the RE trace at Day 88 (Figures 6.11 and 6.12). The abnormally high demand is present for both SCQAS and SSEB (but not for S.E. England). Inclusion of CPW and SRV fails to reduce RE. Despite uninterestingly low CPW and SRV, the synoptic chart for this day (March 29, though not reproduced here, shows a strong NE flow over Scotland (actually very similar to Figure 6.13 (A)). As often happens in such situations, cities in Eastern Scotland, including Edinburgh, Dundee and Aberdeen, are experiencing a very wet, dull and miserable day, with cold rain and strong winds off the North Sea. In contrast, Glasgow is enjoying a relatively sheltered regime, being protected from the North Sea, as confirmed by further examination of 6-hourly Daily Weather Report surface analyses. The raw weather data used to construct the SRV index were from Glasgow, which is why these high windchill
and misery situations of the East Coast do not show up in CPW and SRV at Glasgow. That means Glasgow is not representative in this instance. This points to the need for further investigation of spatial weighting schemes in future work. The spike could also just be a quirk of the model not related to weather effects. Its reason may lie in the weather-insensitive industrial and commercial sectors of the energy market, though it is there for gas and electricity in Scotland. This suggests a connection with weather events, and that some hidden subtlety in the mesoscale weather pattern is the culprit. Its existence has not been satisfactorily explained here, but it does seem reasonable to speculate the above mesoscale influences.

So, windchill (CPW) and misery (SRV) are controlled by the synoptic and mesoscale weather pattern. This effect has shown to be significant generally and sometimes crucially (on extreme events). Various types of evidence have been used to support or calibrate the statistics. Synoptics and statistics have been entirely complementary here.

6.5.4. SUMMARY OF IMPROVEMENTS DUE TO CPW AND SRV

To briefly summarise the need for windchill and misery, and to bring together the relative importance of all the different components of energy demand, Table 6.10 collates complete analyses of variance (in terms of % breakdown) for all energy data sets. By virtue of the additive properties of variances (variance of sum = sums of variances), each row sums to exactly 100%.

Table 6.10: Relative apportionment of % variance explained by all components and meteorological parameters

<table>
<thead>
<tr>
<th></th>
<th>Weeklies</th>
<th>Seasonals</th>
<th>Short-term</th>
<th>Random, unexplained</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>TDEV</td>
<td>CPW</td>
</tr>
<tr>
<td>SEEB</td>
<td>36.6</td>
<td>48.1</td>
<td>10.3</td>
<td>0.8</td>
</tr>
<tr>
<td>NTGAS</td>
<td>10.1</td>
<td>59.5</td>
<td>21.0</td>
<td>2.5</td>
</tr>
<tr>
<td>SSEB</td>
<td>40.4</td>
<td>42.7</td>
<td>8.4</td>
<td>3.1</td>
</tr>
<tr>
<td>SCGAS</td>
<td>20.6</td>
<td>44.2</td>
<td>20.6</td>
<td>4.5</td>
</tr>
</tbody>
</table>
The weeklies and seasonals were dealt with in depth in the appropriate Sections. Short term temperature changes (TDEV) explain most of the variance in DDEV (deweeked and deseasonalised demand). CPW accounts for a further significant percentage of the remaining variance, once TDEV has been allowed for, as we saw in RE(1) vs CPW. Table 6.10 shows gas to be rather more sensitive to intra-weekly temperature variability (of the order of 20% of variance, electricity 10%). Gas is also relatively more susceptible to windchill variations on the daily time scale. Both are possibly due to the greater dominance of the domestic sector of the market for gas, via space heating (Appendix 1).

The remaining separate meteorological variables (SUN, VIS, RD) are poorly correlated with DDEV and add nothing to % variance explained on their own, but from the physical reasoning in Section 5.9.3 scaled values of these were combined into an index having a significant correlation, and which explains a further 1% or so. This, too, we saw when regressing RE(2) on SRV. One would perhaps expect the misery index to account for more of the variance in electricity DDEV than gas, because of lighting. This is true for London and the S.E, but Scottish Gas shows a marked susceptibility to misery (obviously not via lighting demand). This confirms the many other social/psychological arguments in favour of SRV's construction here.

It is particularly revealing to echo this information in a different way by expressing %IRE as a % of raw demand. Table 6.11 testifies to the improvement when adding CPW and SRV, by displaying these successive reductions.

Table 6.11. Stepwise percentage reductions in mean absolute residual errors due to CPW and SRV

<table>
<thead>
<tr>
<th></th>
<th>%(\text{IRE}(1))</th>
<th>%(\text{IRE}(2))</th>
<th>%(\text{IRE}(3))</th>
</tr>
</thead>
<tbody>
<tr>
<td>SEEB</td>
<td>1.8</td>
<td>1.7</td>
<td>1.4</td>
</tr>
<tr>
<td>NTGAS</td>
<td>3.2</td>
<td>2.7</td>
<td>2.7</td>
</tr>
<tr>
<td>SSEB</td>
<td>2.0</td>
<td>1.6</td>
<td>1.4</td>
</tr>
<tr>
<td>SCGAS</td>
<td>2.7</td>
<td>2.3</td>
<td>2.1</td>
</tr>
</tbody>
</table>
The reductions in REI are internally consistent with Table 6.10, and are remarkable when one remembers we would really expect to be at the noise level after TDEV and CPW. Equally remarkable, if we assume domestic tariffs (4.52p/KWh, 33.5p/therm), then to a first approximation 1% of total load (see Table 6.10) is equivalent to 33,000 and 13,000 pounds/day for SSEB and SCGAS respectively. Though not energy production costs, these are the closest approximation to the potential saving using SRV. For CPW, the financial savings are of the order of 0.1 million pounds/day, and TDEV even larger (approaching 0.75 megapounds/day).

It is now totally justified to adopt these indices for demand forecasting. We may shortly proceed to the demand predictions themselves. Firstly we must consider how we simulate weather forecast errors to make the model wholly operational.

6.6. RANDOM SIMULATION OF METEOROLOGICAL FORECAST ERRORS

6.6.1. PHILOSOPHICAL JUSTIFICATION

We will shortly be making demand predictions for the second half, using meteorological forecasts. We will run such a predictive model in two quite different though complementary modes. One assumes perfect weather forecasts for the second half, the other uses forecasts of temperature and windspeed subject to random errors. The latter is much more realistic, since normally in an operational environment the input to the model will be erroneous TA and U forecasts, not actuals. Running in both modes is very valuable because comparison of the output permits an assessment of how well we have modelled the process-response (weather-demand) relations. To subject TA and U to stochastic forecast errors is a harsh test, but it makes the method very powerful and wholly operational if the model withstands this.

In essence, we will be generating a hypothetical series of random TA and U forecast errors, which may be added to the actuals to simulate imaginary erroneous
temperature and wind forecasts. These random weather forecast errors should possess approximately the same statistical properties (mean, standard deviation and distribution) as published values in the literature. Hence we need to conduct a short survey of previous investigations to decide on such values for our simulation.

6.6.2. PREVIOUS LITERATURE ON WEATHER FORECAST VERIFICATION

This Section is not intended to be a comprehensive review, but rather a succinct general guide for values to be used, and to give the reader a feel for the sort of values obtained elsewhere. Hereafter, we shall abbreviate temperature and windspeed forecast errors by TFE and UFE respectively. We will be concentrating almost exclusively on forecasting with lead times of one day (T+24).

There have been several contributions assessing temperature forecast accuracy; much less frequently have windspeed verification studies emerged. Most studies make subjective comparisons with persistence forecasts, show seasonal variations in accuracy, or split TA and U into bands. The Handbook of Weather Forecasting (Met. Office, 1975) provides reviews summarising accuracy of empirical methods of predicting TMAX and TMIN, see also Metaxas (1979). For example, Steele et al (1969) quote rms TFE of 1.9 deg C, Gordon and Virgo (1968) quote 2.2 deg C and Schmidt (1960) 2.1 deg C, all testing the accuracy of empirical methods, and mostly TMIN. Most studies find TFE and UFE to be near normally distributed, but Thompson (1976) works with skewed distributions for hourly electricity predictions in California. Gregson (1982), of Prestwick Airport Weather Centre, in a paper read before a Wind Symposium at Edinburgh University, confirms windspeed forecast errors to be near normal.

Amongst the most interesting of the relevant American literature is Klein and Lewis (1970). They report mean absolute TFE of 2.3 deg C (computer forecasts of TMAX and TMIN) for 60 U.S. cities over 18 months, and rms TFE of 2.9 deg C for 131 American cities. Russo et al (1964) quote mean modulus UFE of 4.0 knots and rms UFE of 5.2 knots, for lead
times of 7 hours at an airport in Connecticut (6 years data). Turton and Harper (1973), in the proceedings of an Institute of Gas Engineers meeting, evaluate weather forecast accuracy for short-term gas demand prediction, but the results are not published.

The most prominent contributions for our purposes are those of Morris (1981 and 1982). Morris (1982) investigated the accuracy of LWC temperature forecasts for the gas industry. He quotes mean modulus TFE of 1.6 deg C (1980 data) for T+24 forecasts. Morris (1981) is one of the few windspeed verification studies to appear. He was assessing accuracy of computer windspeed and waveheight forecasts for spot locations on the Continental Shelf for the Offshore Industry. He reports mean absolute UFE of 6 knots for Montrose, Scotland (3 years data).

6.6.3 STATISTICAL VALUES FOR THE STOCHASTIC SIMULATION

So, only rarely are mean 'actual' TFE and UFE and standard deviations published. It is precisely these we need for the forthcoming simulation of TFE and UFE, not mean modulus errors, so we must seek elsewhere.

Information gleaned from Glasgow Weather Centre (personal communication) provides us with such values. They quote mean actual TFE of -0.22 deg C with standard deviation of 2.17 deg C. These are averages of TMAX and TMIN (24 hour lead times) for the period Jan–Mar 1981, which is very close to our requirements. They also assure that mean actual UFE are almost zero (spot daily forecasts for Glasgow) and that only very rarely (1 in 100) are they >10% out. This was translated here as being equivalent to: 99% of all UFE lie within 0±10% U̅, where U̅ is mean actual windspeed (10 knots for our wind arrays). Since the standard error of U is \( \frac{\sigma}{\sqrt{N}} \), then 99% of all UFE fall within 0±3*\( \frac{\sigma}{\sqrt{N}} \), and \( \frac{3*\sigma}{\sqrt{N}} = 1 \) knot, hence \( \sigma \) is 3.2 knots. Glasgow Weather Centre also confirm all these errors to be near normal (private communication).

The above means and sigmas will be used for random simulation for both Scotland and S.E. England. Though we will subject English TA and U to the same errors, these
values are the closest we can get, and represent a best approximation for our purposes in this particular application.

6.6.4. THE ARTIFICIALLY GENERATED RANDOM ERROR RECORDS

We will now generate stochastically an imaginary series of TFE and UFE for the 41 days of the second half (days 50-90). TFE will have mean $-0.22$ deg C, sigma $2.17$ deg C. UFE will have mean 0.0 knots, sigma of 3.2 knots. These are added to the actual TA and U for realistically erroneous weather forecasts. In addition to possessing these statistical properties, the random generation routine will also force these errors to be normally distributed and to be free from serial correlation, though the proof is not given here.

The resulting fictitious TA and U forecasts (TA+TFE, U+UFE) for the second half are displayed superimposed in Figure 6.16. The horizontal line over the first half (actually corresponding to $\overline{TA}$ and $\overline{U}$) is purely for convenience. Examination of days 50-90 confirms the imaginary forecasts of TA and U to generally coincide with actuals, though some poor forecasts do occur, as indeed they do in practice.

6.6.5. ERROR ANALYSIS AND UNCERTAINTIES IN TERMS

A very useful and practical consequence of simulating weather forecast errors is that these are effectively measures of uncertainty or inaccuracy. For operational demand forecasting, it is clearly very important to be aware of sources of error in each term in the model. For the weather-dependence terms this means weather forecast accuracy. This brief but nonetheless important Section performs a total error analysis on the complete weather dependence model (see Appendix 2). The theory of errors is a broad field, hence the forthcoming treatment is only a summary, and the full proof is not given here.

Temperature ($T$, here) and windspeed ($U$) forecasts are subject to simulated stochastic inaccuracies. Since CPW also explicitly incorporates TA, uncertainties in $T$ will also
Figure 6.16: Temperature (TA) and windspeed (U) actuals, with simulated forecasts of TA and U.
feed through or propagate to this term. SRV is here assumed to be free from prediction errors, and will be omitted from this error analysis.

If we remember DDE\(V = a + b\cdot TDEV + c\cdot CPW\), then denoting DDEV by D, it can be shown, by differentiation, that the total relative error or uncertainty in demand (\(dD/D\)), due to errors in T and U, is given by:

\[
dD/D = 1/D*(0.5*b\cdot dT + c\cdot CPW\cdot (k\cdot dU/U + dT/(T-TCOMF))) \quad (6.3)
\]

where: \(dD\), \(dT\), \(dU\) are absolute uncertainties (errors);
\(dD/D\), \(dT/T\), \(dU/U\) are relative (fractional, \%) errors;
\(k\) is wind exponent in CPW (=0.5 here).

The 0.5 arises from \(TE = 0.5\cdot TA(i) + 0.5\cdot TE(i-1)\), i.e. only half of TE (or TDEV) is subject to errors in TA forecasts.

This complete error equation was arrived at by recognising and applying the various additive laws of error combination to sums, powers and products. The derivatives are replaced by finite differences in practice. Clearly, underestimates of TA propagate through to overestimates in demand. Simultaneous errors in both TA and U can counteract or reinforce each other. We must select the worst possible (pessimistic) case of additive combination of errors.

If we plug in some values as examples, and taking \(D, T, U\) in equation (6.4) to be their time means, then an error of just \(+/- 2\) deg C in a TA forecast (assuming U is perfectly accurate), induces a demand prediction error of \(+/- 2.2\%\) for SSEB (in opposite sense to TA error), i.e. an absolute error of about \(+/- 1627\) MWh. Likewise for SCGAS this becomes \(+/- 3.3\%\) (approx \(+/- 128,000\) Therms). Similarly, an error in a windspeed forecast of \(+/- 5\) knots (no TA error and \(T<TCOMF\) for U to be relevnet) propagates relative demand uncertainties of \(+/- 1.4\%\) and \(+/- 0.9\%\) for SSEB and SCGAS. In the worst possible (pessimistic) case, simultaneous TA and U errors combine additively to produce total fractional uncertainties of \(+/- 3.6\%\) and \(+/- 4.2\%\).
Very similar values were found for S.E. England.

These considerations of errors or uncertainties are of crucial importance in energy management, since such margins of error must be taken into account in on-line demand prediction. For instance, the normal criterion for demand prediction error bands is to use $3 \times \text{Sigma}$ of TA and U forecast errors as $dT$ and $dU$ in equation (6.4). These define outer limits of confidence within which 99% of forecast errors will fall. Such uncertainty limits also include standard errors in the model coefficients themselves.

We can now finally move onto the demand predictions, using both perfect and simulated weather forecasts.

6.7. THE FINAL TOTAL DEMAND FORECASTS

At last we reach the climax of the work, and we now present the results of the final total demand forecasts. We will recall that predictions are made of the 41 days of the second half (days 50-90) using model coefficients derived from the first half (49 days), using autoprojected seasonals, the equation being:

\[
\text{Forecast} = \text{Seasonal} + \text{DDEV} = (\text{PROJ} + a + b \cdot \text{TDEV} + c \cdot \text{CPW} + d \cdot \text{SRV}) \times \text{DOWC}
\]

That is, the forecasted short term (inter-daily) weather dependence (DDEV) is added to the autoprojected seasonals, and the DOWC is then added back in (Section 5.15, see also Appendix 2 for complete model equation). The model is totally operational and completely realistic when using simulated weather forecast errors, and very nearly so with perfect weather forecasts (i.e. semi-realistic), for it is derived from wholly independent data. This is like testing the model's applicability to other data sets.

Quantitative objective measures of forecast skill/ measures of success and verification schemes were developed in Chapter 5 and were applied in both modes, as we now present.
6.7.1. MODEL OUTPUT USING PERFECT WEATHER FORECASTS

6.7.1.1. STATISTICAL PRESENTATION OF RESULTS

The following Table summarises some of the results of model runs in the perfect weather forecast mode, for all energy data streams, graphical results will follow later.

Table 6.12: Model performance verification and forecast skill statistics, assuming perfect weather forecasts, for totally independent predictions of the 2nd half; and model coefficients

<table>
<thead>
<tr>
<th></th>
<th>SEEBO</th>
<th>NTGAS</th>
<th>SSEB</th>
<th>SCGAS</th>
</tr>
</thead>
<tbody>
<tr>
<td>r</td>
<td>0.98</td>
<td>0.93</td>
<td>0.93</td>
<td>0.82</td>
</tr>
<tr>
<td>rms PC</td>
<td>1.8%</td>
<td>4.2%</td>
<td>2.9%</td>
<td>4.6%</td>
</tr>
<tr>
<td>FE</td>
<td>-53 MWh</td>
<td>-74 T. Th</td>
<td>-923 MWh</td>
<td>-63 T. Th</td>
</tr>
<tr>
<td>Zo</td>
<td>-0.21</td>
<td>-1.42</td>
<td>-2.91</td>
<td>-2.29</td>
</tr>
<tr>
<td>z</td>
<td>0.03</td>
<td>0.38</td>
<td>0.85</td>
<td>1.00</td>
</tr>
<tr>
<td>a</td>
<td>-4237</td>
<td>-246</td>
<td>-7368</td>
<td>-526</td>
</tr>
<tr>
<td>b</td>
<td>-1757</td>
<td>-326</td>
<td>-915</td>
<td>-80</td>
</tr>
<tr>
<td>c</td>
<td>10</td>
<td>10</td>
<td>127</td>
<td>10</td>
</tr>
<tr>
<td>d</td>
<td>33</td>
<td>-2</td>
<td>30</td>
<td>1</td>
</tr>
</tbody>
</table>

Table 6.12 contains a large amount of information, and the reader may wish to refer back to the reference list of variables to remind himself/herself of the definitions of the forecast skill measures. Note too that residual errors (RE) have now been replaced by true forecast errors (FE), which are fundamentally quite distinct.

These results are indeed very encouraging, especially for electricity, and show the model to behave very well, bringing rms FE down as low as 1.8% for SEEBO. The results compare very favourably with accuracies currently quoted in the literature. In fact, the SEEBO rms FE of 1.8% is actually
somewhat lower than the rms FE of 2.5% quoted by Baker (1977) for CEGB daily load prediction. The r value of 0.98 for SEEB shows exceptionally close correspondence of actuals with predicted demands. In this case, only 4% of the variance in demand is left unexplained (residual variance).

It would appear from Table 6.12 that electricity is somewhat more predictable than gas, and this is consistently so between regions. This is possibly because of the greater influence of illumination on lighting, though we did demonstrate the need for SRV for both fuels. This could also be because the weekly cycles are more pronounced for electricity. They explain almost double the variance (Section 6.2), and so are inherently much more predictable. This is more likely than greater sensitivity to the weather, since weather dependence (as measured by multiple r) was shown to be remarkably similar between the two fuels throughout the analysis.

South-East England is also rather more predictable in terms of its energy usage, for both electricity and gas (Table 6.12). This is certainly due to greater weather sensitivity, as was demonstrated in the multivariate case studies. This apparently greater sensitivity arises from the relative dominance of commercial/domestic loads in the S.E., and heavy industry in Scotland.

Electricity is once again seen to be more susceptible to SRV (via lighting). The relative unimportance of misery for NTGAS (but not SCGAS) is reflected in its negative d coefficient (Table 6.12). This too is consistent with other types of evidence given earlier. Though we showed SRV to be consistently important for all other data streams, for NTGAS it might be better only to switch it on at extremes, but not to drop it completely. NTGAS could perhaps be alerted only when relatively extreme misery situations are expected. Probably SRV does not always operate for NTGAS in any case. One would need many more years data to ascertain whether this was a systematic effect.

The root mean square percent error (rms PC) is a very useful measure of relative forecast accuracy, for it possesses the important property of comparibility between
different data sets, and the work and results of different people. Here, it tells us that for SEEB, for example, we will on average (in rms sense) be out by 1.8% (1455 MWh). This is probably the most useful skill statistic in the Control Rooms. Its usefulness lies in that it is synonymous with standard deviation of FE, if $FE=0$. If we are to predict tomorrow's demand, we can be 95% certain that our % FE will fall within $2 \times$ rms PC of the mean actual FE ($=0$) and 68% sure it will lie within 1 rms PC of zero. This is extremely useful for operational purposes in that it tells us something about the mean and expected range of FE, assuming such probabilities remain constant over time.

The Zo test (Section 5.8.2) indicates that $FE$ is not significantly different from zero for the S.E, but for Scotland Zo is significant at 95% (Table 6.12). This indicates that we might have a systematic bias in our predictions (overestimates in this case). Zo is, however, strongly affected by extremes and the z test (Chapter 2), which is less sensitive to extreme values, confirms that RAW and FC are not significantly different (i.e. they belong to the same population), see Table 6.12. Hence we cannot assume any systematic bias, but it is interesting that for all energy data bases, there is a slight systematic demand overestimate ($-\text{ve } FE$ in Table 6.12). The industries do prefer slightly negative FE, since these are less expensive to deal with than consistent demand underestimates.

6.7.1.2 GRAPHICAL PRESENTATION OF RESULTS

To supplement these statistics and to provide graphical support for them, Figures 6.17 and 6.18 present the actual and forecast demands, for all four energy data streams. The closeness of fit and general correspondence is striking, and some predictions are almost spot on. The greater predictability of the S.E, and of electricity for both regions, is readily apparent.

If anything, the model does have a slight tendency, for SSEB only, to overpredict some weekend values, though not significantly (see Table 6.12). The reasons for this are not at all obvious, and methods of overcoming it were
Figure 6.17: Actual (RAW) and forecast (FC) daily SEEB and NTGAS demands, using perfect weather forecasts
Figure 6.18: Actual (RAW) and forecast (FC) daily SSEB and SCGAS demands, using perfect weather forecasts.
fruitless. What we believe we are seeing here is a subtle manifestation of the DOWC scheme: it could result from not using daily b values to temperature-correct before deweek ing (higher sensitivity at weekends, etc). It was not statistically justified to do this with data sets of this size, though without doubt it would with larger data bases. Sample size proved to be a frustrating limitation in this respect. This is pure speculation, however, and is very tentative. It does appear to be a feature peculiar to the SSEB data, and is trivial compared to weather forecast errors, as we will soon show.

6.7.1.3. FORECAST ERRORS, WINDCHILL AND MISERY

Before moving on to simulated weather forecasts, Table 6.13 brings together some further important statistical evidence of successive improvements in actual forecast errors (not RE), on adding CPW and SRV. It also gives cross correlations of FE (not RE) with these parameters.

Table 6.13: Cross correlations of forecast errors (FE) with CPW and SRV, and stepwise improvements in forecast accuracy due to CPW and SRV, for 2nd half; electricity units in MWh, gas 1000 therms

<table>
<thead>
<tr>
<th></th>
<th>SEEB</th>
<th>NTGAS</th>
<th>SSEB</th>
<th>SCGAS</th>
</tr>
</thead>
<tbody>
<tr>
<td>FE(1) vs CPW</td>
<td>0.67</td>
<td>0.54</td>
<td>0.60</td>
<td>0.57</td>
</tr>
<tr>
<td>FE(2) vs SRV</td>
<td>0.68</td>
<td>0.19</td>
<td>0.36</td>
<td>0.17</td>
</tr>
</tbody>
</table>

\[ FE(1) \] = 2078 (2.6%) 310 (4.4%) 2490 (3.7%) 190 (5.4%)
\[ FE(2) \] = 1781 (2.3%) 249 (3.5%) 2038 (3.0%) 152 (4.3%)
\[ FE(3) \] = 1343 (1.7%) 268 (3.8%) 1746 (2.6%) 148 (4.2%)

Since residual errors have now become true forecast errors, this is a real test of the need for windchill and misery in a forecasting situation. All correlations in Table 6.13, except SRV for gas, are significant at 99%. They are
not only remarkable (since we are testing the model developed on the first half on independent data) but are considerably higher than those with RE (Table 6.11). For electricity, SRV is almost as important as CPW (as measured by r), which unambiguously proves their blatant importance when forecasting.

The stepwise reductions in mean modulus forecast error are also clear from Table 6.13, except that SRV slightly worsens |FE| for NTGAS. In that case, if misery was dropped (though it should still be brought in on extremes), then all measures of forecast accuracy would reduce to the |FE(2)| case in Table 6.13.

It could be that the dependence of FE on CPW and SRV has now become non-linear, so far we have implicitly assumed it to have remained linear. To confirm that this linearity still holds, scatterplots have been produced to act as visual support to the linear regressions. Figure 6.19 presents such scatterplots for RE(1) vs CPW and RE(2) vs SRV, both for SSEE. The data points do not visually cluster in any part of the plot, except slightly along the limitation of SRV=100. The dependence is noticeably linear. Any refinements that improve the model in these ways must be retained and explicitly incorporated.

The final forecast errors, FE(3), have all been thoroughly tested and show negligible persistence and certainly no cyclical behaviour (except slightly for SSEE, as discussed). More importantly, they show no weather dependence. Though the results of all these tests are not shown here, examples will be given later.

6.7.1.4 ULTIMATE PREDICTABILITY OF ENERGY DEMAND

What is the best we could ever hope to achieve in forecasting daily energy demand? Is there an "ultimate predictability"? These questions are of fundamental philosophical interest and will concern us in the concluding Chapter, where we will be making suggestions as to possible model improvements, and questioning whether any improvements are indeed achievable. This latter can only be answered by considering ultimate predictability. If we assume perfect
Figure 6.19: Scatterplots of FE(1) vs CPW for SEEB and FE(2) vs SRV for SEEB, for days 50-90 (2nd half)
weather forecasts, then the ultimate predictability will be
given by that accuracy, if we have modelled the processes
correctly.

Kane and Brownfield (1977) and Lehman and Warren
(1978) claim that the upper theoretical limits of demand
predictability are demonstrably not determinable.

It is becoming clear that, at least for electricity,
we must be getting quite close to the ultimate
predictability of demand, since here we are assuming
theoretically perfect weather forecasts. Any remaining
errors in the model will be trivial compared to the effects
of realistic errors in weather forecasts.

6.7.2. MODEL RUNS USING SIMULATED WEATHER FORECAST ERRORS

6.7.2.1. DEMAND FORECAST SKILL VERIFICATION

In this mode, the model is totally operational and
uses no data at all from the second half to predict it.
Table 6.14 collates the most important and relevant measures
of forecast accuracy for this mode.

Table 6.14: Demand forecast skill verification using
randomly simulated temperature and
windspeed forecast errors, for 2nd half.

<table>
<thead>
<tr>
<th></th>
<th>SEEB</th>
<th>NTGAS</th>
<th>SSEEB</th>
<th>SCGAS</th>
</tr>
</thead>
<tbody>
<tr>
<td>r</td>
<td>0.96</td>
<td>0.87</td>
<td>0.90</td>
<td>0.77</td>
</tr>
<tr>
<td>rms PC</td>
<td>2.7%</td>
<td>5.8%</td>
<td>3.2%</td>
<td>5.1%</td>
</tr>
<tr>
<td>FE</td>
<td>-254 MWh</td>
<td>-93 T. Th</td>
<td>-778 MWh</td>
<td>-52 T. Th</td>
</tr>
<tr>
<td>Zo</td>
<td>-0.67</td>
<td>-1.28</td>
<td>-2.13</td>
<td>-1.63</td>
</tr>
<tr>
<td>z</td>
<td>0.14</td>
<td>0.48</td>
<td>0.70</td>
<td>0.79</td>
</tr>
<tr>
<td></td>
<td>FE(1)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>3.5%</td>
<td>6.2%</td>
<td>3.9%</td>
<td>5.7%</td>
</tr>
<tr>
<td></td>
<td>FE(2)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>3.2%</td>
<td>4.9%</td>
<td>3.2%</td>
<td>4.8%</td>
</tr>
<tr>
<td></td>
<td>FE(3)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>2.6%</td>
<td>5.1%</td>
<td>2.9%</td>
<td>4.7%</td>
</tr>
</tbody>
</table>
Naturally, there is a general reduction (though not significant) in predictability, as we would expect using erroneous temperature and windspeed forecasts (compare Tables 6.12 and 6.14). Moving down Table 6.14: once again we observe greater forecast accuracy for South-East England, and for electricity for both Scotland and England. The accuracy for SEEB is still strikingly high ($r=0.96$), in this case only 8% of the variance remains unexplained. Mean actual forecast errors ($\bar{FE}$) are again consistently slightly negative, the advantages of this have been detailed. The $Z$ statistic is only significant for NTQAS, and $z$ is never significant, hence once more we can assume no systematic bias. Yet again, CPW and SRV serve to improve forecast accuracy substantially, in both absolute and percentage terms, except SRV for NTQAS.

One would perhaps expect results to differ between different stochastic simulations. Very rewardingly, the results are insensitive to different random simulations, e.g. $r$ consistently varies by no more than 0.01 between various simulated runs.

As an example of the graphical output from simulation mode, Figure 6.20a gives the demand actuals and forecasts for SEEB (the rest being very similar). The closeness of correspondence is still very much apparent, and some predictions are still spot on. There is no apparent visual systematic difference between actuals and forecasts, but this must be rigorously tested statistically (and will be).

Figure 6.20 also gives the FE(1), FE(2) and FE(3) traces superimposed, for SEEB, as we did with RE. If we compared the spikes and troughs with synoptic and mesoscale weather patterns, we would indeed find a correspondence again. The associated cross correlation statistics of these FE with CPW and SRV were given in Table 6.13, though for perfect weather mode. We can readily observe from the FE traces (Figure 6.20b and c) the successive reductions in FE as stepwise account is taken of CPW and SRV. Note that the FE(3) record is the final forecast errors using 3 variables (TDEV, CPW, SRV), which we will be working with later.
Figure 6.20: a) Actual and predicted SEEB demands using simulated TA and U forecast errors; b) The FE(2) and FE(3) traces for SEEB; c) FE(1) and FE(2) records for SEEB.
6.7.2.2. MODEL ERRORS VS WEATHER FORECAST ERRORS

One may perform a very useful comparison between the results of perfect and simulated weather modes, by cross reference between Tables 6.12 and 6.14. The reduction in demand forecast accuracy we can assume to result purely from using erroneous weather forecasts. The errors when using perfect weather forecasts must be those in the model itself, i.e. "model errors", as we shall call them, and one cannot blame these on inaccurate weather forecasts. These are errors due to inadequacies in our representation of trend, seasonality, weeklies, and others inherent in the model formulation itself. Barnett (1972) reports global CEGB demand prediction errors to be almost equally divided between model errors and weather forecast errors.

Cross reference between Tables 6.12 and 6.14 reveals rms % errors to increase by about 1/2, 1/3, 1/10 and 1/4, for each energy array therein. Hence the ratio of model errors to weather forecast errors is about 2:1, 3:1, 10:1 and 4:1 for SEEB, NTGAS, SSEB and SCGAS respectively. The higher values for Scotland may mean we have not modelled the processes as well for Scotland (notably SCGAS), where inaccurate weather forecasts seem relatively subordinate. Much more likely, this probably results from the greater weather sensitivity of the South East (proven throughout) and hence inherently greater potential for accurate modelling thereof. SEEB's ratio of 2:1 compares favourably with that of 1:1 obtained by Barnett (1972).

6.7.2.3. FINAL FORECAST ERROR ANALYSES

The final forecast error trace, FE(3), for SEEB was given in Figure 6.20b. All FE(3) series were found to be quasi-stationary (almost white noise) and approximately normally distributed, with no periodicity embedded in them. As an example, the final Figure and graphical evidence, Figure 6.21 gives visual output from spectral analysis, superposed epoch analysis, autocorrelation and normality tests, for SEEB's FE(3). The correlogram on Figure 6.21a shows zero persistence in these final forecast errors. The probability distribution (Figure 6.21b) indicates no serious
Figure 6.21: The final forecast errors, FE(3), for SEEBS:

a) Correlogram; b) Frequency distribution;
c) Superposed epoch analysis d) Spectrum.
departures from normality and certainly displays no skewness. As is usual in these applications, it becomes desirable to check whether any cyclical behaviour with a 7-day frequency remains in the final forecast errors. The Acf in Figure 6.21a has already shown there to be none. As additional confirmation, Figure 6.21c shows the results of putting FE(3) through a univariate superposed epoch analysis for SEES. There is clearly an absence of any cycles with period 7 days, as testified by the absence of any visually systematic pattern in the day-of-week means. Harmonic analysis provides supplementary evidence, and the spectrum in Figure 6.21d shows no particular wavenumber to dominate (wave 3 is spurious and insignificant, and only explains 1% of the variance). This indicates no periodicity at any frequency. In particular, wave 6, corresponding to the weekly cycles for this series of 41 days, is very feeble.

Equally important, the final forecast errors (FE(3)) do not appear to exhibit any dependence on weather effects. It is unlikely that the model can be improved, therefore, by further parameterisations of the meteorology. The variability of demand due to the weather is fortunately far greater than any source of error in the data or uncertainties in terms. Such sources of error, and further critical evaluation, will be discussed in the concluding Chapter, in relation to possibilities for further model refinement and suggestions for future work. We have probably done all we can (on the weather-dependence side) towards modelling and understanding how we respond to the weather in terms of our energy requirements, and hence how we can predict future energy demand using meteorological data.
CHAPTER 7
CONCLUSIONS, PROBLEMS AND SUGGESTIONS FOR FUTURE RESEARCH

So, can the meteorologist contribute towards making financially worthwhile energy savings using meteorological data? Well, the answer is most certainly YES. This Chapter discusses this claim.

Various detailed conclusions and problems have been presented separately in each Chapter, as appropriate to individual case studies. This concluding Chapter represents a brief summary of the main conclusions to the daily case studies in Chapters 5 and 6. Though most of it is structured as a critical evaluation of the daily model therein, it does contain three distinct sections. First, we present a general philosophical discussion of how the case studies hang together, and then achievements of daily modelling in general. Explicit suggestions for improving the model then follow, after which we put forward some more general recommendations for future work. The model's merits have been adequately covered, and its structure and parameters justified. These need not be repeated here, it only remains to detail the model's defects and deficiencies.

7.1 GENERAL DISCUSSION OF ACHIEVEMENTS

We will open the discussion with the question: why should we ever want to model and forecast energy consumption? To save money by planning the efficient use of heating and generating plant (i.e., optimise the energy management system), and to avoid catastrophic model failures in severe weather resulting in power cuts, etc. Very worthwhile monetary savings can be realised with improved knowledge of customer reaction to weather.

The thesis as a whole has had a dual purpose of modelling energy demand (to understand human response) and predicting energy demand using meteorological data. We have taken a fresh look at this problem by consideration of several time and space scales. The importance of spatial/temporal hierarchies (orders), and of physical meaning, has been emphasised throughout. It is indeed rewarding that the same laws of process–response manifest themselves across
several scales. The results in general testify to the high degree of order or predictibility embedded in energy time series. That is, we do appear to be able to predict the overall behaviour of a large group of consumers (regional level of aggregation), despite the millions of individual responses being very complex, personal and inherently unpredictable. We have really been trying to seek order or regularity in what seems at first like apparently chaotic noise. The study has also made a contribution to applied statistics and energy literature, via the statistical analysis of meteorological and energy data on several scales.

Chapter 1 contained a comprehensive survey of mainstream and internal literature, and the motivation and philosophy behind the study. The statistical Chapter on the theory of multiple time series analysis then followed. Chapter 3 then presented the results of a national case study of monthly coal and oil consumption. Chapter 4 summarised a local scale investigation of weekly gas and oil demand for two individual groups of buildings at Edinburgh University. This contained some significant applications to energy conservation. Though important and interesting in themselves, Chapters 3 and 4 effectively played a supporting or complementary role to Chapters 5 and 6. They were part of the necessary build up in understanding daily data.

The daily case studies of forecasting regional electricity and gas demand in Chapters 5 and 6 represent the work at its most useful, and are really the climax or heart of the study. The model developed there is totally operational and can be used for on-line, short term demand prediction. This is a very important and practical real-world problem in energy management (actually Operational Research), and is one where considerable financial savings can be achieved. In Chapter 5 the model development was described in detail. Chapter 6 then applied this theory in practice to two Scottish and two English regional case studies. The residual errors approach derived there proved very useful in looking at occasions when the Area Boards are caught out.
The present generation of models suffers on extreme occasions. These "wild forecast days" all have one thing in common: the fact that they correspond with severe or sudden synoptic or mesoscale events. When using temperature alone, models exhibit errors which show a dependence on synoptic situation, via the interaction of CPW and SRV with demand. A rewarding consequence of the work is that these synoptic comparisons justify the meteorological parameters.

Hence the study has conclusively demonstrated that it is very worthwhile to incorporate other variables besides (effective) temperature, such as CPW (windchill statistic) and SRV (misery index). The empirical SRV index is unique, and TE and CPW are partially novel. In addition to temperature, then, the importance of windspeed, solar radiation/sunshine, visibility and rainfall duration was teased out via these supplementary parameters. There are many subtleties built into these indices, and it is these sophistications that enable us to quantify how we perceive our weather in relation to fuel usage. The systematic dependence of errors on synoptic situation was then explained by reference to various windchill or misery situations. We have put forward a unique combination of several types of evidence (visual, graphical, synoptic) to support or complement the statistics. This greatly encourages and facilitates the extraction of physical meaning. Statistical and synoptic evidence have been married rather than divorced, and naturally go hand in hand with physical interpretation. This study represents a first attempt (as far as the author is aware) of using synoptic situation to calibrate the statistics in energy research. Recognition of the intimate relation between meteorological physics and applied statistics will always allow deeper physical understanding of weather sensitivity, and hence greater predictibility.

It was shown to be particularly useful and instructive to run the model in two modes, using perfect and randomly simulated weather forecast errors (temperature and windspeed). The whole model formulation is believed to be original, though some techniques were not entirely novel.
Multivariate models of this type appear to describe quite adequately the aggregate response of people on the regional scale. The usefulness of distinguishing between model errors and weather forecast errors was highlighted. It was shown that at least for electricity we must be getting quite close to the "ultimate predictibility" of demand. This raises the important and fundamental question of whether any significant improvements are attainable. The author's view is that it is unlikely that any worthwhile physically-based improvements are achievable for these applications. It is almost certainly not worthwhile undertaking any further parameterisations of the meteorology. Several preliminary experiments performed by the author have supported this claim. Assuming we have an adequate response model of the meteorology, the statistical model itself could possibly be improved, as we now show by considering sources of error.

One could continue building in more and more of the physics and non-weather components (e.g. industrial), but initial attempts to do so were fruitless. The more detail one pursues, the more subtlety one uncovers, and there comes a point when the degree of sophistication or complexity is adequate for our purposes.

7.2 RECOMMENDATIONS FOR MODEL REFINEMENTS

In science, we must always report failures as well as successes. Hence it is now time to consider the model's problems and weaknesses, to level criticisms at the formulation, and to suggest avenues of future research relating to model improvements. The suggestions are not in order of importance, are not mutually exclusive, and not collectively exhaustive. The critical evaluation as a whole is necessarily only a summary of the main points for tidying up and further development of the model.

1) Substantiation on new daily data: The existing daily model needs to be substantiated on new daily data sets, to see if it misbehaves, and as confirmation of its reliability and applicability. Remembering these runs were for only 90 days, it is felt desirable to continue testing the model on longer data sets, including summer and winter, though
preliminary runs on summer data were not productive (no windchill in summer). A model is only as good as its data base, and this is one of the disappointing, sometimes frustrating, things about lack of data. Longer data sets would permit the desirable use of daily temperature dependencies when temperature-correcting prior to deweekng.

2) **Hourly data:** The fundamental statistical framework of the daily model is such that it could be fairly easily adapted to cope with hourly demand forecasting. The data would either be "dedayed" to remove the daily cycle, in an analogous way to "deweek" or "deseasonalise", or else separate runs on each individual hour would be made. Hourly demand is even more weather-sensitive and would be particularly useful for exploring the impact of the sudden arrival of travelling synoptic or mesoscale disturbances/weather systems in the mid-latitude westerlies, by, e.g., plotted British Isles charts. The application of catastrophe theory to understand hysteresis loops in consumer response (Chapter 5) would also be an interesting exercise.

3) **Sector modelling:** Errors will arise due to the multitude of non weather sensitive end-uses of energy (e.g. industrial, commercial). Sector and sub-sector modelling would therefore be desirable, e.g. on just the domestic space-heating sector or lighting. Limitations of data availability on load-mix in this country at present restrict this experiment.

4) **Microscale studies:** Further feasibility studies on individual buildings (family homes, flats) or groups of buildings (housing estates, office blocks), as in Chapter 4, would be useful.

5) **Spatial weighting schemes:** Demand data are for large areas (typically), whereas meteorological data are for single points (always). Research on areal-averaging schemes for the meteorological data is a pressing need.

6) **Different weather parameterisations:** This also is a possibility, but it is doubtful whether it would result in significant improvements on data sets this size. For example, one could experiment with a variety of cut-offs, or switch the parameters on or off at arbitrarily selected times.
thresholds, e.g. lighting variables would be dropped for demands occurring in darkness. One useful experiment would be to construct CPW and SRV only from extremes, or at least use discrete bands of TA or U.

7) Different synoptic selection criteria: Some alternative conditions for choosing the synoptic situations are possible. For instance, one could subjectively classify or categorise forecast errors in terms of airmass or synoptic type, though our scheme was objective.

8) Further simulation of weather forecast errors, e.g. for SRV (though errors in TE and CPW were stochastically generated here). Whether this would improve performance remains an open question.

9) Updating model coefficients: The model coefficients, DOWC's, etc, could be continuously updated (daily). This would allow sensitivity to "drift" with short and medium term changes in response. Though computationally slower, effectively all sensitivity would always be up to date.

10) Box–Jenkins methods: Further exploration of this suite of models is potentially worthwhile, as alternative representations of trend, seasonality, weeklies, etc. It would be premature to say whether this would improve forecast accuracy, but this aspect does warrant some investigation, despite computer–time considerations (slow convergence of iterations, etc).

11) More realistic management criteria, such as the margins of error suggested in Chapter 5, should be pursued further in testing whether improvements have been made.

12) Medium–term applications: The daily autoproduction scheme could fairly easily be extended to deal with demand projections out to lead–times of several days.

7.3. FUTURE WORK ON ENERGY METEOROLOGY IN GENERAL

The most promising area of future research to advance the science of energy meteorology, and that which has produced the most encouraging results so far, would seem to be regional case studies of daily and hourly electricity and gas demand. The use of meteorological data should certainly be re–examined in cases of current model failure, especially
in severe, critical, sudden or marginal synoptic/ mesoscale events. The area of work that most urgently requires attention is high windchill and misery situations. It is difficult to avoid the conclusion that the forecast errors and synoptics approach to complement the statistics would be the most beneficial. This philosophy would represent a compromise between meteorology and statistics. Whatever the approach, any modelling strategy should be geared towards sensitivity studies, and ultimately to demand forecasting.

It is maintained here that the meteorologist’s greatest single contribution to future energy saving lies in further empirical verification of the physics through case studies. Further Government work and interest on this is at present hindered by a massive nationwide energy conservation programme. This study could possibly come under the heading of energy conservation management, since conservation should begin with a better physical understanding of the nature and scale of consumer response to weather, and not necessarily advertising campaigns.

We will close with the thought that worldwide shortages of energy are expected from about the year 2000 onwards, and with the prospect of dwindling supplies of fossil fuels on this planet in general. Accordingly, energy conservation (and alternative energy technologies, not considered here) is very important. A final comment regarding this warning would be that sadly the present body or pool of knowledge fails to recognise the importance of meteorological information here. Unfortunately, there is little interest and hence a paucity of active work done on this as a consequence. Paradoxically, there is an accepted and growing need for such research amongst energy management circles: in central Government (Department of Energy), industry (Area Boards), and academia. It is hoped that this contribution will go some way in helping to remedy this deficiency, to use meteorological data for more accurate predictions of energy sales, better energy management and hence improved standards of thermal and visual comfort (heating and lighting).
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APPENDIX 1: CUSTOMER CLASS BREAKDOWN OF ENERGY MARKET

Breakdown of energy load-mix (sales) by:

a) Customer class/sector, left-hand pie-charts, e.g. 50% of all heat supplied to domestic sector is met by gas;
b) Fuel type, right-hand pie-charts, e.g. 35% of all electricity sold is destined for domestic sector

After Department of Energy, 1979. The shaded and annotated slices (added by author) refer to tabulated sub-sectoral load-mix on following page.
APPENDIX 1: CUSTOMER CLASS BREAKDOWN OF ENERGY MARKET

TABULATED SUB-SECTORAL LOAD-MIX (to supplement pi-charts)  All %’s rounded

A: DOMESTIC GAS
Cooking * 8% (4)
Space heating * 69% (34)
Water heating 22% (11)

B: DOMESTIC ELECTRICITY
Cooking * 10% (4)
Space heating * 27% (10)
Lighting * 8% (3)
Refrigeration 14% (5)

C: INDUSTRIAL ELECTRICITY
Lighting 6% (2)
Motive power 65% (24)
Process heating 13% (3)

D: COMMERCIAL ELECTRICITY
Air conditioning * 8% (2)
Space heating * 46% (12)
Water heating 8% (2)

* indicates weather-sensitive sub-sector
# inc. Street/Public lighting

Percentages in brackets refer to % of all sectors, e.g. 34% of all gas sold is for domestic space heating (elec’ 10%)

After Electricity Council and BGC Annual Reports

Domestic sector includes: family homes, flats, farms and other private residential dwellings
Commercial sector includes: shops, offices, banks, schools, hospitals, hotels, public houses and other places of entertainment.

ADDITIONAL USEFUL ENERGY STATISTICS

Fuel share of CENTRAL HEATING MARKET

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<td>Natural Gas</td>
<td>64%</td>
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<tr>
<td>Electricity</td>
<td>22%</td>
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<tr>
<td>Coal</td>
<td>10%</td>
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<td>Oil</td>
<td>3%</td>
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After Scottish Gas, 1980

Total ELECTRICITY SUPPLIED to public supply system (DoE, 1982)

<table>
<thead>
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<th>Source</th>
<th>Share</th>
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<td>Thermal (coal or oil-fired) stations</td>
<td>85.0%</td>
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<tr>
<td>Hydro-electric plant (free and pumped storage schemes)</td>
<td>2.1%</td>
</tr>
<tr>
<td>Nuclear power stations</td>
<td>12.8%</td>
</tr>
<tr>
<td>Private industrial producers (mainly steel, chemicals)</td>
<td>&lt;0.1%</td>
</tr>
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APPENDIX 2: THE TOTAL DAILY DEMAND FORECASTING MODEL

\[ F \times DPROJ = \frac{TE-TPROJ}{U^*k(TCOMF-\alpha)} \times \left(-\text{SUN/10.2+RD/1220} \right) \times \left(-\text{VIS/58.4+2} \right) \times \left(33 \right) \times \left(\text{SEASONAL} + a + b \times \text{TDEV} + c \times \text{CPW} + d \times \text{SRV} \right) \times \text{DOWC} \]