

List of Tables

Table 3.1 Sales to Customer Class in 1990.....	3.7
Table 3.2 Population and Sample Sizes.....	3.8
Table 3.3 Population and SRS Sample Size.....	3.9
Table 3.4 Population and Sample Characteristics.....	3.10
Table 3.5 Predetermined Sample Precisions.....	3.11
Table 3.6 Bulk Sample Adjustment.....	3.14
Table 3.7 MBSS Precisions of Disaggregation Samples.....	3.16
Table 3.8 Coincident Peak Contributions.....	3.21
Table 3.9 Key Statistical Indicators.....	3.21
Table 5.1 Descriptive Statistics of Error Profiles.....	5.9
Table 6.1 Seasonal Correction Factors.....	6.2
Table 6.2 Annual Maximum Demands and Load Factors for the Moderate Forecast.....	6.11

Figure 5.3 Average Winter Week Error Profile for 1991.....	5.4
Figure 5.4 The Tariff E Load Shifting Correction Profile.....	5.4
Figure 5.5 Ave Winter Week Error after Tariff E Correction.....	5.5
Figure 5.6 Error Distributions for the 1991 Forecast.....	5.6
Figure 5.7 Demand Profile of Recently Electrified Community.....	5.7
Figure 5.8 The Uncorrected Error Profile for 1992.....	5.8
Figure 5.9 The Error Profile for 1992 Corrected for Load Shifting.....	5.8
Figure 5.10 Total Load Shifting.....	5.10
Figure 6.1 Excel Implementation of XDFM.....	6.1
Figure 6.2 The Improved Demand Profile Forecasting Process.....	6.4
Figure 6.3 Improved Demand Profile Forecasting Model.....	6.4
Figure 6.4 Tariff T Profile Shape.....	6.6
Figure 6.5 XDFM Model Error 1993.....	6.6
Figure 6.6 1993 Error Profile with Tarif E Load Shifting.....	6.7
Figure 6.7 1993 Error Profile with Tariffs E and T Load Shifting.....	6.7
Figure 6.8 Sectoral Energy Sales based on Moderate Forecast.....	6.8
Figure 6.9 Forecast Average Winter Week Demand Profiles.....	6.9
Figure 6.10 Average Week LDCs for each Season for 2000.....	6.10
Figure 6.11 Moderate Growth Forecast Annual MDs and Load Factors	6.12
Figure 6.12 Tracking of the Annual MD by the XDFM model.....	6.12
Figure 6.13 Annual MDs for the Three Forecasts.....	6.13

Figure 3.7 1990 Average Winter Weekday Demand Profile of Traction.....	3.18
Figure 3.8 1990 Average Winter Weekday Profiles of Peak Customer Classes.....	3.18
Figure 3.9 System Disaggregation of the Average Winter Weekday 1990..	3.19
Figure 3.10 Comparison of Actual and Modelled System Demand Profile.....	3.20
Figure 3.11 Proportional Peak Contributions of Customer Classes.....	3.22
Figure 3.12 Tariff E Load Shifting.....	3.23
Figure 4.1 Monthly Class Sales in 1990.....	4.5
Figure 4.2 Average Winter Week Demand Profile for 1990.....	4.6
Figure 4.3 Average Winter Week Load Duration Curve for 1990	4.6
Figure 4.4 Eskom Weekly Peaks for 1992 to 1994.....	4.7
Figure 4.5 Clustering of Weekly LDCs.....	4.8
Figure 4.6 The Aggregation Model.....	4.9
Figure 4.7 Components of a Disaggregation Model.....	4.10
Figure 4.8 The Basic Demand Profile Forecasting Process.....	4.11
Figure 4.9 Basic Demand Profile Forecasting Model.....	4.11
Figure 4.10 Seasonal Sales Variations.....	4.14
Figure 4.11 The Quatro Implementation of XDFM.....	4.15
Figure 4.12 The Prototype Average Winter Week for 1990.....	4.16
Figure 5.1 The XDFM Error Analysis Process.....	5.2
Figure 5.2 Average Winter Week Profile Error for 1990.....	5.3

List of Figures

Figure 2.1 Forecasts by Milton and Troost.....	2.2
Figure 2.2 Eskom Annual Sales 1955 to 1993.....	2.4
Figure 2.3 Eskom Annual Sales and Forecasts.....	2.7
Figure 2.4 Eskom's Long Term Forecasting Process in 1992.....	2.10
Figure 2.5 Assumed Load Factor MD Forecast.....	2.11
Figure 2.6 Eskom Annual Load Factor 1955 - 1993.....	2.13
Figure 2.7 The Relationship between Morning Peak and Annual Sales.....	2.14
Figure 2.8 Evening Peak Growth.....	2.15
Figure 2.9 Eskom's Changing Customer Composition 1955 - 1993.....	2.16
Figure 2.10 The Electrification Program.....	2.16
Figure 2.11 Load Shifting by Tariff E Customers.....	2.17
Figure 2.12 Migration of Electricity Sales Between Tariffs.....	2.18
Figure 2.13 Limits of assumed Load Factor Forecasting.....	2.19
Figure 2.14 Proposed Long Term Forecasting Process.....	2.20
Figure 3.1 Class Aggregation Process.....	3.2
Figure 3.2 A Disaggregation Model.....	3.2
Figure 3.3 The Eskom Customer Pyramid in 1990	3.4
Figure 3.4 Marketing Customer Classification.....	3.5
Figure 3.5 Revised Customer Classification.....	3.6
Figure 3.6 1990 Average Winter Weekday Profiles of Base Customer Classes.....	3.18

4.4.3 The System Demand Profile	4.14
4.5 IMPLEMENTING THE MODEL	4.14
4.5.1 The first (prototype) demand profile forecasting model	4.14

Chapter 5 - Testing the Prototype XDFM Model

5.1 THE OBJECT AND METHOD OF THE TESTING PROCESS	5.1
5.1.1 The Test Method	5.1
5.2 TESTING THE BASE YEAR - 1990	5.2
5.3 TESTING THE FORECAST YEARS 1991 AND 1992	5.3
5.3.1 Measuring Additional Load Shifting in 1991	5.3
5.3.2 Measuring the Impact of Electrification in 1991	5.6
5.3.3 Measuring the Load Shifting in 1992	5.9
5.3.4 The Electrification Impact in 1992	5.9
5.4 - CONCLUSION	5.9

Chapter 6 - Forecasting with the XDFM

6.1 EXPANDING THE MODEL FOR FORECASTING	6.1
6.1.1 Additional Load Classes	6.1
6.1.2 Improving the SCF Factors	6.2
6.2 MODELLING TARIFF IMPACTS	6.3
6.2.1 The Tariff Impact sub-models in XDFM	6.3
6.2.2 Testing the Load Shifting Sub-Models	6.5
6.3 LONG TERM FORECASTING WITH XDFM	6.8
6.3.1 Demand Profile Forecast	6.8
6.3.2 Scenario modeled for the 1996 Demand Profile Forecast	6.9
6.3.3 Seasonal Average Week Demand Profile Forecast	6.10
6.3.4 XDFM Annual Maximum Demand Forecast	6.11
6.3.5 Probability Distribution of the XDFM Annual Peak Demand	6.13
References	R.1

3.6.2.1 The 'Random' Aspect	3.11
3.6.2.2 The MPU Focus of Standard Sample Validation Tests	3.11
3.6.3 Subjective Sample Validation	3.11
3.6.4 Further Validation of the 'Bulk & Other' and 'Developing Community' Classes	3.13
3.6.5 Testing of the Modelled System Demand Profile	3.15
3.6.6 Sample Validation with DPFM Sample Design Error Ratios	3.15
3.7 THE DISAGGREGATION MODEL IMPLEMENTATION	3.16
3.7.1 Validation of the Model	3.19
3.7.2 Coincident Peak Contributions	3.20
3.8.3 Annual and Summer Models	3.21
3.8.4 The Demand Impact of Tariff E	3.21
3.9. PROJECT EVALUATION	3.22
3.10. CONCLUSION	3.24

Chapter 4 : The Experimental Demand Forecasting Model (XDFM) Development

4.1 ALTERNATIVES TO THE ALF METHOD	4.1
4.1.1 Econometric Peak Demand Models	4.2
4.1.2 Disaggregation Models	4.2
4.1.3 End-Use Hourly (Aggregation) Models	4.2
4.1.4 The Contribution to Load Factor (CLF) Method	4.3
4.1.5 The Most Suitable Method for Eskom	4.3
4.1.6 A Note on Confusing Terminology	4.4
4.2 REPRESENTING THE ESKOM SYSTEM DEMAND PROFILE	4.4
4.2.1 The Representation of System Demand Profile for the Model	4.4
4.2.2 The Requirements of the Users of the Model	4.5
4.2.3 Analysis of the System Demand Seasonal Components	4.7
4.2.4 The Representation for XDFM	4.8
4.3 THE AGGREGATION MODEL PROCESS AND STRUCTURE	4.9
4.3.1 The Aggregation Model Process	4.9
4.3.2 Demand Profile Forecasting Structure	4.10
4.4 DATA FOR THE XDFM MODEL	4.13
4.4.1 Class Demand Profile Shapes	4.13
4.4.2 Class Energy Sales Figures	4.13

2.1.7 Norman 1977 & 1982	2.3
2.1.8 The Sales Growth Discontinuity of 1982	2.4
2.1.9 Recommendations of the De Villiers Commission of Enquiry, 1984	2.5
2.1.10 Joubert G 1985	2.6
2.1.11 Davison 1990	2.9
2.1.12 Prinsloo 1992	2.9
2.1.13 Berrisford 1993	2.10
2.1.14 Assumed Load Factor MD Forecasting	2.11
2.2. STRUCTURAL CHANGES IN ESKOM'S DEMAND PROFILE	2.12
2.2.1 The Sales Growth Discontinuity of 1982	2.12
2.2.2 Declining Annual Load Factor	2.12
2.2.3 The Evening Peak Growth	2.13
2.2.4 Factors Affecting the Structure of the Eskom Demand Profile	2.15
2.2.4.1 Changing Customer Composition	2.15
2.2.4.2 The National electrification Program	2.15
2.2.4.3 Tariff E . The first step into DSM	2.17
2.2.4.4 Time-of-Use (TOU) Tariffs Proposed and Implemented	2.18
2.3. THE GOALS OF THIS RESEARCH PROJECT	2.18
2.3.1 The evaluation of the present process	2.18
2.3.2 Conclusions	2.19
2.3.3 The Goals of this Project	2.20
<u>Chapter 3 - The System Disaggregation Project</u>	
3.1 INTRODUCTION	3.1
3.2 PROJECT OBJECTIVES	3.1
3.3 PROJECT OVERVIEW	3.1
3.3.1 The Electrical Load Structure	3.3
3.3.2 Tariff Structures and Metering	3.3
3.3.3 Data Available for the Disaggregation Project	3.4
3.4 CUSTOMER CLASSIFICATION	3.4
3.5 THE SAMPLES	3.7
3.5.2 A Sample Design Exercise	3.8
3.6 SAMPLE VALIDATION	3.9
3.6.1 Testing Validity as Simple Random Samples for MPU Expansion	3.10

Contents

Declaration	i
Abstract	ii
Acknowledgements	iii
Contents	C.1
List of Figures	F.1
List of Tables	T.1

Chapter 1 - An Overview of Demand Forecasting

1.1. INTRODUCTION	1.1
1.1.1 Forecasting, Uncertainty, and this Project	1.2
1.1.2 Requirements for Forecasting in Utilities	1.2
1.1.3 The Applications of Long Term Forecasting	1.3
1.2 A HISTORICAL PERSPECTIVE ON LONG TERM LOAD FORECASTING IN ELECTRIC UTILITIES	1.4
1.2.1 In the Beginning...	1.4
1.2.2 Early Maximum Demand Forecasting	1.5
1.2.3 The Advent of Econometric Models	1.5
1.2.4 The Need for Improving MD Forecasting	1.7
1.2.5 The Development of Aggregation (End-Use Hourly) Models	1.7
1.2.5.1 The ECLS Project and other early end-use models	1.8
1.2.5.2 The Development of HELM	1.8
1.2.5.3 Other End-Use Aggregation Forecasting Models	1.9
1.2.5.4 Alternative Maximum Demand Forecasting Techniques	1.9
1.2.6 Scenario Planning and Uncertainty Evaluation	1.10
1.2.7 Current Long Term Utility Forecasting Practise	1.10
1.2.8 The Future of Long Term Forecasting in Utilities	1.11
1.3 THE STRUCTURE OF THIS DISSERTATION	1.12

Chapter 2 - Demand Forecasting in Eskom

2.1 LONG TERM FORECASTING TECHNIQUES USED IN ESKOM	2.1
2.1.1 Milton 1947	2.1
2.1.2 Troost 1956	2.1
2.1.3 Fenwick and Torr 1961	2.1
2.1.4 Straszacker 1966	2.2
2.1.5 Joubert J T 1971	2.2
2.1.6 Stoffberg 1975	2.3

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Abstract

Accurate forecasting of system Maximum Demand (MD) is vital to Eskom. Under-estimating the MD could result in a generation capacity shortage, with devastating consequences for the economy. Similarly, a high MD forecast would result in overcapacity, with expensive generating plant standing idle. The traditional method of MD forecasting in Eskom has become unreliable due to a changing relationship between forecast energy sales and expected maximum demand. The reasons for the changing system demand profile were isolated and analysed. Alternative MD forecasting techniques are evaluated and end-use hourly aggregation models were identified as a method suitable for Eskom. An experimental demand profile forecasting model was developed, using data from a previous project. The model was tested and proved able to cope with the structural changes in the system demand profile. This resulted in the adoption of this technique by Eskom and approval for the development of a full scale demand profile forecasting model.

Declaration

I declare that this dissertation is my own unaided work. It is being submitted for the Degree of Master of Science in Engineering in the University of the Witwatersrand, Johannesburg. It has not been submitted before for any degree or examination in any other University.

A. J. Berrisford

A. J. Berrisford

22 day of February 1997.

**The Development of a Demand Profile Forecasting
Model for Eskom, with Particular Emphasis on
the Estimation of the Demand Impact
of Time Differentiated Tariffs**

Andrew John Berrisford

A dissertation submitted to the Faculty of Engineering, University of the Witwatersrand, Johannesburg, in fulfilment of the requirements for the degree of Master of Science in Engineering.

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countries also do not depend on low electricity prices for a global competitive advantage, as does South Africa. The author also notes that in the USA, one of the undesirable consequences of deregulation has just started to occur. There have been two blackouts in the US in recent months - and with no obligation to supply, it is difficult to lay the responsibility or accountability at the door of the utility. **The free market makes no guarantee for the supply of the commodity.** The author suspects that a purely market driven ESI may have a short life in places like the USA when customers are unable to get electricity. It is likely that a market driven ESI may require a different form of regulation to limit price extremes and ensure supply. This would imply an ongoing need for long term planning and some form of IEP process. The change may be that it is the regulator rather than the utility that performs this function.

1.3 THE STRUCTURE OF THIS DISSERTATION

The rest of this dissertation covers the development and testing of the Experimental demand profile forecasting model (XDFM).

Chapter 2 is a review of forecasting techniques as used in Eskom. The evolution of these techniques and their shortcomings under current conditions provide the background for this research.

Chapter 3 described the disaggregation project which provided the customer demand profile data for the experimental model. It was vital to establish confidence in this data set, as inaccurate customer class demand profile data would raise serious doubt about the XDFM model's test results.

The development of the XDFM model is covered in Chapter 4, followed by the testing discussed in Chapter 5. The last chapter demonstrates the use of the model in Eskom's long term forecasting process and illustrates its performance since 1994.

The success of the experimental model led to support for the development of a full-scale Demand Profile Forecasting Model (DPFM). This development is currently under way and the model is expected to be in use by 1998.

- Scenario Planning followed by End-Use Econometric modelling for Energy Sales Forecasting.
- End-Use Aggregation modelling of selected scenarios for Demand Profile Forecasting. This includes statistical analysis of exogenous impacts like weather.

The entire process includes *explicit quantification of uncertainty*, with the goal of producing a forecast range within which 'least regret' planning decisions can be made, together with contingency plans to cater for less likely but possible alternatives.

1.2.8 The Future of Long Term Forecasting in Utilities

World-wide, the electric utility industry is currently undergoing a revolution which has implications for forecasting. This revolution is encapsulated in the concepts **Privatization**, **Competition**, and **Deregulation**. Large, vertically integrated public utilities are being broken up into components. The Generation, Transmission, and Distribution functions are separated, often with competition introduced at the Generation level and sometimes at the Distribution level. There are many different models of this restructuring in different countries, but the general trend is towards wholesale competition with retail competition as an ultimate goal. The Electricity Supply Industry (ESI) has been operating in this mode for several years in some countries such as Norway while other countries look set to continue operating large utilities such as EdF in France and ENEL in Italy. The ESI in Great Britain was privatised in 1990, and recent legislation in the USA [Richardson 1994] is set to allow competition for customers and open access to transmission systems for Independent Power Producers (IPPs).

This revolution has serious implications for long term forecasting [Landgren 1995]. If a utility has no captive customer base or service territory, and no obligation to supply customers, it may have no need for long term expansion planning or forecasting. If 'market forces' can efficiently regulate the ESI, the type of long term planning traditionally done by utilities for a century could become obsolete. As capacity limits are reached, it is expected that electricity prices will rise until the utility or an IPP finds it financially beneficial to build new plant - in theory. The economy of scale that led to huge central power stations was based mainly on higher efficiencies of larger units, and new technological developments have reduced this advantage in recent years. Modern technology has made it possible to construct small but efficient power plants with relatively short lead times. A 300 MW Combined Cycle power station can be built in under two years [Faruqi & Melendy 1995]. The designs of small (100 MW or less) pebble bed nuclear plants are available [Eskom 1996].

This concept has proved workable in some countries for a relatively short period of time, a few years. It has been applied to other previously nationalised or regulated industries, such as telecommunications and transport. It has also happened to energy service industries, notably gas utilities. The countries in which it appears to work are those where electricity use appears to have saturated, resulting in low growth. These

value distributions and Monte Carlo simulation have been reported [Belzer & Kellog 1993].

1.2.6 Scenario Planning and Uncertainty Evaluation

Increasing uncertainty about economic indicators and customer behaviour, as well as increasing intervention in the market by utilities with DSM measures, led to a new approach during the Eighties. Forecasters shifted their focus from predicting single line forecasts accurately, to a range of likely values quantifying the uncertainty within the range [Gellings 1991]. An EPRI sponsored workshop on forecasting models in 1980 [EPRI 1980] identified the treatment of uncertainty as a primary concern and first evaluated three alternative approaches to evaluating uncertainty, namely **scenario planning, probability trees, and Monte Carlo simulations**. These methods are discussed at length in an EPRI research report [EPRI 1990]. Several case studies of US utilities applying these methods were later described [EPRI 1992]. More US Utilities have since reported their experiences in uncertainty evaluation at several conferences [e.g. Irish 1992b, Logan 1995].

Scenario Planning [Davison 1990] attempted to define a small set of possible economic scenarios for the utility's service area. The scenarios were broadly defined, and each econometric parameter used in the forecasting models was given a value consistent with each scenario. The forecasting models were run for each set of parameters, resulting in forecasts for each scenario. Planners could then develop expansion plans for the 'most likely' scenario, and contingency plans for the other scenarios. Forecasters also started using several techniques together, e.g. time series, econometric, and aggregation, combining the results by averaging or weighting according to confidence in each method [Gellings 1991, Adams 1992, Irish 1992]. Comparing the outcome from a time series forecast with an econometric or aggregation model highlighted some of the shortcomings in one or the other method, enabling the forecaster to improve the final forecast [Gellings 1991].

Scenario planning has been refined by the adoption of techniques to evaluate the uncertainty of some assumptions and to determine the sensitivity of the forecast to variations in input parameters. Methods used include Probability Tree Analysis [Gellings 1991] and Monte Carlo Simulation [Belzer & Kellog 1993]. The use of probabilistic rather than deterministic methods in forecasting has spread to the expansion planning process itself. A recent paper describes three approaches to implementing probabilistic expansion planning, namely deterministic equivalent, scenarios, and stochastic optimization [Giorenstin et al 1993]. One of the models used by Eskom for expansion planning and production costing, EGEAS, uses the stochastic optimization approach.

1.2.7 Current Long Term Utility Forecasting Practice

The current state-of-the-art in long term forecasting is a combination of the following techniques:

model. HELM gained widespread support in the US, with about 50 utilities using it by 1986 [Irish & Maxwell 1986]. A growing range of HELM applications has since been reported [Dorsey 1987, Inglis & Adams 1992]. Currently over 200 US utilities use HELM.

Although Eskom was aware of its existence, the lack of customer or end-use demand profile data in South Africa and the adequate performance of existing forecasting techniques dictated against its obtaining this model. (In 1986 Eskom management still felt that the low growth since 1982 was transient, and that high growth rates would return.)

In 1993 HELM was rewritten as a Windows based PC package, and Eskom was busy negotiating an affiliation agreement with EPRI. The author developed a spreadsheet-based disaggregation model, using class demand profile data from a 1990 cost-of-service disaggregation project [Bluff 1992a & b] to test the concept of hourly aggregation models for Eskom. This model was tested against the system demand profiles of 1990 to 1993 and shown to be capable of discerning the changes and their causes. The adoption of HELM for Eskom was proposed [Berrisford 1994a] and subsequently accepted.

1.2.5.3 Other End-Use Aggregation Forecasting Models

The hourly end-use approach was gaining ground in other countries at the same time. A disaggregation model for medium term (seven years) hourly demand profile forecasting was reported by the CTGB [Allera & McGowan 1986] in the UK. The model dealt with weather impacts by using weather normalised end-use demand profiles and was run for each of several typical days with half-hour intervals. More recent examples include the DELMOD aggregation model developed in New South Wales, Australia [Bartels et al 1992].

1.2.5.4 Alternative Maximum Demand Forecasting Techniques

In recent years several alternatives to end-use hourly models have been proposed. These have all been attempts to improve on the ALF method without the high costs of end-use hourly models. There are two basic approaches, namely:

- Improving the ALF accuracy by **combining weighted load factors for each customer class**, to cater for changing customer mixes and load management impacts. This approach is first seen in 1972 as applied by the CTGB [UNIPED 1972]. It was 'reinvented' in 1990 and reported at the AIEC Load Research symposium [AIEC 1990].
- The application of statistical techniques to the distribution of annual peaks and their relationship to annual energies, average seasonal peaks, or other load parameters. Since weather is a major factor affecting demand peaks, this often takes the form of weather impact analysis. Recently techniques using **extreme**

Parti & Parti [Parti & Parti 1980] was used by several utilities to generate residential end-use profiles from whole house demand profiles (e.g. AIEC 1990b, Bartels et al 1992). This statistical technique produced good results in some cases but not in others [Gellings 1991].

The load research data and end-use models made it practical to implement end-use hourly aggregation models. The concept of maximum demand forecasting simultaneously developed to cover more than just a single estimate of the annual peak demand. It implies rather a range or distribution of maximum demand probabilities, and includes load shape forecasting and load duration curve forecasting as well.

1.2.5.1 The ELCS Project and other early end-use models

One of the first serious attempts at end-use aggregation modelling was the **Electric Load Curve Synthesis (ELCS)** project undertaken at PSE&G (in California) in 1980 [Gellings & Taylor 1981]. ELCS forecast about 160 components of the system load, including weather sensitive end-uses and using hourly weather data. The model forecasts hourly demand for 30 years, but summarizes the annual demand profiles into two seasons and three day types per season. This approach is common to aggregation models, simultaneously taking advantage of similarities in daily demand profiles and reducing the size of data sets considerably. This model was used very successfully by PSE&G, and its versatility in dealing with weather impacts, DSM, and load management programs generated a lot of interest.

Broehl reported the development of a similar model [Broehl 1981]. This had two sub-models, one of which was an end-use aggregation model for the residential, commercial and industrial sectors. The Electricity Council in the UK also started using this technique, initially modelling the end-use demand profiles of residential customers [Skinner 1984]. Unfortunately a lack of good end-use load research data hampered the widespread use of these models at the time.

1.2.5.2 The Development of HELM

The Electric Power Research Institute (EPRI) later developed an improved end-use hourly aggregation model, initially termed the **Load Shape Forecasting Model** in 1984 (LSF) [Dickson 1984] and later called the **Hourly Electric Load Model (HELM)** [EPRI 1985]. The LSF had an hierarchical structure, with user-defined end-uses being aggregated to Class Loads, which were then aggregated to get the System Load. End-uses could be weather sensitive or insensitive, and LSF could forecast class or system load shapes for different weather scenarios [Dickson 1984]. A model to develop weather sensitivity parameters from demand and weather data was not included, and the user had to establish these parameters externally. LSF could also forecast the impacts of load management and conservation programs.

HELM was initially written as a mainframe application, and five US utilities submitted system data to EPRI to test the model during development [EPRI 1985]. The model was an enhancement of the LSF, including a weather sensitivity sub-

1.2.4 The Need for Improving MD Forecasting

A major shortcoming of the ALF method is the lack of demand profile shape information it provides for expansion planners. Although MD forecasts inform planners of the future capacity required, they do not provide any information on the optimal capacity mix required. Typically historic system demand profiles are used as indicative of future system demand profile shapes. This was a reasonable assumption before load management, time variant tariffs, and DSM programs appeared - all of which can change system demand profile shapes.

Despite considerable detail and complexity, econometric models could not deal with changes in system demand profile shapes. These data-intensive monuments to computer modelling could not cope with the increasingly unpredictable changes in the electricity industry. This applied particularly to peak demand requirements. The key shortcoming was the inability of econometric models to cater for diversity and the impacts of increasing load management and conservation DSM programs.

1.2.5 The Development of Aggregation (End-Use Hourly) Models

As it became clear that the more complex econometric models did not necessarily produce more accurate forecasts, particularly for system maximum demands, sectoral (or segmentation) hourly models were developed [Broehl 1981, Irish & Maxwell 1986, Gellings 1991]. Initially the lack of detailed data limited these to a top down (**disaggregation hourly**) approach, but in recent years emphasis has fallen on developing bottom-up (**aggregation or end-use hourly**) models. These models forecast daily average demands or hourly demand profiles for each end-use and sum (**aggregate**) these to simulate the system demand profile. These were used in conjunction with econometric energy sales models to forecast system maximum demands and demand profiles. The models attempt to develop the utility demand profile as the sum of all the electric end use consumption patterns. The assumption is that the use for any given end-use appliance will be consistent, and the appliance penetration can be established by means of surveys. The future energy requirement for each end-use is then modelled using econometric techniques and scaled profiles summed in the aggregation model. This approach can capture the changing fortunes of different end-uses and cater for changing customer mixes. Hourly end-use models can more accurately forecast maximum demands and changes to the system demand profile shape. Loads that contain weather sensitive components can be separated into weather sensitive and weather-independent end-uses, which can be represented separately in the aggregation model [Schick 1988]. The Econometric approach and aggregation models can be described as 'causal objective' types [Armstrong 1985].

The availability of load research data increased during the Eighties, and simultaneously several 'physical' or 'engineering' end-use models were developed. The most popular 'physical' models include those developed by the US Department of Energy and LOADSIM developed by EPRI [EPRI 1983, 1987], although several others have been described [Calloway & Brice 1982, Ihara & Schweppe 1981]. During the same period the **Conditional Demand Analysis (CDA)** technique developed by

as a result of regulatory requirements [Irish & Maxwell 1986, Gellings 1991]. These programs, often with conflicting impacts on the system demand, distorted the previously stable relationship between energy sales and system maximum demand. Eskom was not seriously affected by the oil crisis, as Eskom does not use oil as a primary fuel for electricity generation. During the same period other utilities in Europe, such as the CEEGB in the UK, were facing unpredicted changes in electricity usage patterns by their customers, in particular residential customers [Armstrong 1985], as a result of saturations of some appliances and the introduction of more efficient technologies. The introduction of load management programs by utilities further influenced growth in unexpected ways. Electricity demand growth patterns no longer followed historic trends, patterns or cycles.

These changes resulted in the next phase of forecasting technique development. Recognizing that electricity sales growth was a function of economic growth, and further that sales to different sectors was related to economic activity in those sectors, forecasters developed econometric models [EPRI 1976] to supplement their time series models. The first econometric models looked at the system level only (**macro econometric models**), but they soon developed into end-use variants which forecast energy needs in each sector separately (**end-use or sectoral econometric models**) [Peck & Weyant 1985]. Econometric models could accurately characterize the behavioural relationships that represent market decisions based on relative prices and costs. This includes estimating the impacts of DSM programs [Irish & Maxwell 1986]. Although these generally improved sales forecasts, peak capacity requirements derived from them did not improve.

Some utilities started experimenting with econometric models in the late Sixties. Econometric models introduced a 'promising new methodology' according to the FPC [FPC 1969]. The UNIPEDE manual [UNIPEDE 1972] described 'conditional models' which were macro econometric regression models. It is apparent that both Italy and Great Britain were using simple econometric models at the time.

Inaccurate forecasts, usually high in the US [Gellings 1991], resulted in high electricity rates as utilities built more generating plant than they could use once construction was complete. The forecasters' econometric models became more sophisticated in an attempt to cope with these structural changes [Gellings 1991]. A major development was residential and commercial end-use models based on combinations of econometric and **engineering (physical) models** to forecast end-use energy processes separately and collate them to get system total energy requirement forecasts. Popular examples of these models include the Residential End-Use Energy Planning System (REEPS), Commercial Residential End-Use Energy Planning System (COMMEND) and Industrial End-Use Planning Methodology (INDEPTH) all developed by EPRI [Gellings 1991]. This set of models represents the apex of development of end-use econometric models for utility forecasting. They are still in use and EPRI still runs training courses on them.

sales forecasts with acceptable results. These time series models have been classified as '**naïve objective**' techniques by Armstrong [Armstrong 1985].

Time series models have the inherent advantages of relative simplicity and limited data requirements, since the only input required is also the output, i.e. monthly or annual electricity sales. Techniques used include [Bielech 1992, Armstrong 1985] :

- Extrapolation (linear, exponential)
- Curve Fitting
- Smoothing
- Moving Averages
- Auto Regression
- Autoregressive Integrated Moving Average (ARIMA) or Box-Jenkins models

Often combinations of the above techniques are used. Time series forecasting software packages usually include several techniques, which allow the user to exploit the advantages of each. A good example of such a package is Forecast Master [EPRI 1991]. This program includes a range of time series and econometric modelling tools.

1.2.2 Early Maximum Demand Forecasting

Prior to the 1973 oil crisis, annual maximum demand (MD) forecasts were derived by simply applying an Assumed annual Load Factor (ALF technique) to the energy sales forecasts. This approach, while very simple, proved adequate for many years. The primary underlying assumption of a stable energy / demand relationship, was consistent until the oil crisis.

Approximately half of the responding utilities in the FPC report [FPC 1969] derived MD forecasts from the energy forecast, using the ALF technique. The remainder forecast MDs separately, extrapolating historic values with some adjustments. It is apparent from the UNIPED manual [UNIPED 1972] that, for many European countries at the time, the primary capacity constraint was not maximum demand but energy. Ensuring enough generation capacity for forecast energy requirements thus always ensured MD requirements. The manual details an enhanced ALF technique used by the CEEB (UK) to derive their annual MD forecast. (The CEEB had introduced off-peak tariffs several years previously and was one of the first utilities to experience load shape changes as a result.) The CEEB had a effective Load Research facility, and had noticed changes in the annual load factors of different classes of customer, due to the off-peak tariffs. They therefore forecast the load factors of the coincident demand for each class, derived a coincident peak for each class using the forecast sales and LF, and summed these to obtain a forecast of the system peak demand.

1.2.3 The Advent of Econometric Models

In the wake of the 1973 oil crisis, many utilities in the USA introduced energy conservation and load management programs (Demand Side Management or DSM).

These two facts combined make long term forecasting an inescapable necessity, despite the considerable difficulty in predicting events long into the future.

1.2 A HISTORICAL PERSPECTIVE ON LONG TERM LOAD FORECASTING IN ELECTRIC UTILITIES

Although the focus of this dissertation is demand profile forecasts, the strong link between demand forecasts and energy forecasts requires some insight into the historical evolution of electricity sales forecasting. The methods discussed will not be dealt with in any great detail.

1.2.1 In the Beginning...

Energy sales forecasting techniques in utilities evolved from subjective, 'gut-feel' estimates a century ago, when the first power stations were constructed. These rather **subjective** techniques then developed through simple extrapolations to time-series techniques in the Sixties [Stanton et al 1969, Irish & Maxwell 1986, Gellings 1991, Bleloch 1992]. These methods were no longer subjective, but the models assumed that the future could be predicted adequately by projecting historic patterns into the future.

A study of electric utility load forecasting techniques [FPC 1969], produced for the US Federal Power Commission (FPC) in 1969, reports that one third of thirty responding utilities used judgemental forecasting and another third used simple extrapolation based on linear or exponential trends. Four of the thirty reported the use of correlation or rudimentary econometric models. The report describes early attempts to separate the weather sensitive load component from the total load, creating a probabilistic peak demand model.

A UNIPED manual on electricity forecasting methods in 1972 mentions an observation that is "so general that it is sometimes taken as having a force of law : this is the famous 10 year doubling law" [UNIPED: 1972]. Apparently it was generally accepted that electricity demand doubled every ten years. The authors of this report were from Germany, Italy, Spain, Belgium, France and England - this must have been a widely applicable law ! The manual describes 'autonomous' forecasting methods, which include linear and exponential extrapolation, and introduces the idea of market saturation with a logistic forecasting model. Although the manual indicates that sales growth was still exponential, it anticipated saturation in the future.

For decades electricity demand growth in industrialized countries grew strongly, consistently, and predictably; and time series techniques performed adequately. No thought was given to dynamic market forces or causal factors that affect the demand for electricity [Irish & Maxwell 1986]. Forecasts on the high side were considered acceptable, as it was believed that demand would inevitably grow to meet any excess capacity, while low forecasts were considered serious problems [Irish & Maxwell 1986]. Throughout this period maximum demand forecasts were derived from energy

use is scheduling of generation plant to produce the required energy as cheaply as possible.

- **Medium Term** - Weekly or monthly energies and MDs for a period of one to five years ahead. These data are needed for planning and budgeting over the business planning horizon, and for planning the primary resources a utility needs - coal and water.
- **Long Term** - Annual energies and MDs for 10 to 30 years ahead. The construction of new power stations takes from 8 to 15 years, from planning to commissioning. Future electricity demand therefore needs to be known and planned for long in advance. Long term forecasts are usually updated on an annual basis.

This dissertation is concerned primarily with long term forecasting, and covers the following aspects:

- A survey of demand forecasting methods used by overseas utilities, and their applicability to Eskom.
- An review of the techniques of energy sales and annual MD forecasting techniques as used in Eskom.
- The development and testing of a prototype model using the disaggregation approach, using the limited data available in the organisation at the time.

An important assumption underlying this research is that Eskom will remain essentially a vertically integrated public utility for several years. The value and need for a Long Term Demand Profile Forecasting Model could be perceived to be significantly diminished in a privatised and competitive electricity supply industry. This is discussed in more detail later.

1.1.3 The Applications of Long Term Forecasting

Large public electricity utilities have two fundamental reasons for requiring long term forecasting, with horizons (ten to thirty years) that appear ridiculous for most businesses. These are the following:

- **Long Construction Lead Times** - The benefits of economies of scale apply strongly where a utility has access to large quantities of cheap coal, as in the case of Eskom. The large 'Six Pack' power stations that are most economical for base load generation in South Africa take over ten years to complete once the decision to proceed has been made. This implies that Eskom must be confident of the energy and demand requirements a decade before they materialize.
- **Obligation to Supply** - Public utilities usually have a monopoly in their area of supply. In return for this captive and secure market, they are also obliged to supply all the electrical energy requirements in their 'franchised' area of supply. Eskom currently carries this obligation.

and predict the load shifting by Eskom's customers in response to Tariffs E and T (recently renamed Nightsave and Megaflex or Miniflex).

1.1.1 Forecasting, Uncertainty, and this Project

It has been said that the only certainty about forecasts is that they will be wrong. Some, however, will be more accurate than others. Forecasting is as much an art as a science, with the science component gradually increasing as more is understood of the reasons for changes in the forecast quantities. Mark Twain is reported [Harding 1991] as having said the following regarding forecasting :

"In the space of 176 years, the lower Mississippi has shortened itself 242 miles. That is an average of a trifle over one mile and a third per year.

Therefore, any calm person who is not blind or idiotic, can see that in the Old Oolotic Silurian Period, just a million years ago next November, the lower Mississippi River was upward of 1 300 000 miles long.

By the same token, any person can see that 742 years from now, the lower Mississippi will be only a mile and three-quarters long.

There is something fascinating about forecasting. One gets such wholesome returns on conjecture out of such trifling investments of facts."

This author, like Mark Twain, is not a forecaster, and had a rather cynical view of forecasters and their tools. While studying changes in the Eskom system demand profile, the author became aware of the simplistic approach Eskom forecasters had used for annual maximum demand forecasting, and proposed a better method [Berrisford 1993b]. The proposal was accepted and led to the development [Berrisford 1994a] of a model that is better able to cope with the current changes occurring in the Eskom system demand profile. This dissertation describes that project.

1.1.2 Requirements for Forecasting in Utilities

Electric utilities have a range of different requirements for forecasting. These include operational demand forecasting, energy sales, maximum demand (MD), and revenue forecasting. There are three classes of energy and demand forecasting. Each has it's own time horizon, accuracy requirement, and update rate. These can be loosely grouped into the following categories:

- **Short Term** - Hourly demand values for a day (24 hours) to a week ahead, normally updated daily. These forecasts are required for operating the generation and transmission system, used by the Systems Operations Department. The primary

Chapter 1 - An Overview of Demand Forecasting

1.1. INTRODUCTION

"Prediction is a difficult art, especially when it involves the future" - Neils Bohr

The traditional method of system annual Maximum Demand (MD) forecasting utilised by Eskom has served well for many years, but has proved unable to cope with dynamic structural changes currently occurring within the Eskom system. Energy sales forecasts, usually based on some form of econometric modelling, are used with an assumed future system load factor to derive a forecast MD. This technique, known as the Assumed Load Factor (ALF) method, depends on a long term consistent relationship between a utility's annual sales and MD. This relationship can be disturbed by changes in the customer base of a utility or the introduction of Load Side Management measures by the utility. Within the past decade both of these types of disturbance have taken place in Eskom, and long term MD forecasting using the ALF technique is suspect. Unusually severe winter weather in 1994 resulted in a system peak demand of 24 800 MW (more than 1 000 MW higher than the forecast MD), as well as an unexpected increase in energy sales of about 3%. This has increased the urgency to improve Eskom's forecasting process.

Accurate forecasting of system MD is of vital importance to Eskom. It takes from ten to fifteen years to construct a new power station (from planning to commissioning). Under-estimating the MD could result in an generation capacity shortage, with devastating consequences for the economy. Similarly, a high MD forecast would result in a situation of overcapacity, with expensive generating plant standing idle, resulting in unnecessarily high tariffs. During 1993 the author used data from a system disaggregation done by Load Research in 1991 to illustrate MD forecasting using a disaggregation based model [Berrisford 1993b]. In 1994 he improved and expanded the disaggregation model to produce MD and load duration curve forecasts for Eskom's Integrated Electricity Planning Committee [Berrisford 1994b]. These forecasts have been included in Eskom's Corporate Planning Directives, and led to support for the full scale implementation of a demand profile forecasting model over the next two years [Berrisford 1994a].

This project covers the development of the demand profile forecasting model. It is based on a disaggregation of the system demand profile, incorporating end-use aggregation, weather impact, and tariff impact sub-models as well. This approach combines the simplicity and relatively low cost of the disaggregation approach with the detail and accuracy of end-use aggregation for customer classes experiencing rapid growth, weather sensitivity, or shifting load in response to tariff messages. This research covers the development of the disaggregation model in general, with particular emphasis on the development of a sub-model that can accurately measure

Figure 2.5 illustrates the technique using a load factor of 74% to derive an estimated MD of 27.7 GW from an annual sales forecast of 179 TWh in the year 2000.

2.2. STRUCTURAL CHANGES IN ESKOM'S DEMAND PROFILE

2.2.1 The Sales Growth Discontinuity of 1982

The decline in sales growth in the early Eighties heralded structural changes to the Eskom system demand profile which would have far reaching effects, with consequences similar to those of the 1973 oil crisis for US utilities. Growth averaged about 8% per annum from 1950 till 1981, and then dropped suddenly to about 4% per annum. This sales growth discontinuity is clearly illustrated in Figures 2.2 and 2.3. The fundamental reasons for this change were :

- The reduction in growth of large, energy intensive industrial projects that meant an end to the regular large increases in base load Eskom had experienced over the previous two decades.
- The change in global economic growth trends after the 1973 and 1979 oil crises. This impact was delayed in Eskom's sales growth rate, mainly due to Eskom's dependence on coal rather than oil, and the continuing construction of large energy intensive industries after 1973.

The decline had made electricity sales forecasting almost impossible using macro econometric forecasting methods. It resulted in excess generating capacity which may last till early in the next century. Eskom has been criticised for this situation [Coff 1984, Pouris 1986] and is attempting to improve it's forecasting ability. In the future a far better understanding of each customer sector will be necessary in order to accurately forecast the system growth.

2.2.2 Declining Annual Load Factor

Figure 2.6 illustrates Eskom's annual load factor from 1955 to 1993. A general trend of improving load factors is evident from 1955 to about 1980. This is, it is suspected, due to improving load management by the Mining and Industrial sectors during this period. The trend has, however, exhibited a consistent decline since 1982.

The prototype disaggregation model was improved to become the Experimental Demand Forecasting Model (XDFM) [Bernisford 1994b] and has been used since 1994 to forecast long term annual MDs and load factors for Eskom's IFP planning process. The XDFM demonstrated the advantages of demand profile forecasting. This led to management support for a full scale demand profile forecasting model (DPFM) to be based on the HELM package developed by EPRI [EPRI 1985].

2.1.14 Assumed Load Factor MD Forecasting

The annual load factor for Eskom has varied between 73% and 78% over the last four decades (Figure 2.6), and can change by up to 3% from year to year. Prior to 1993, a single average long term annual LF (e.g. 74%) was assumed, and the annual MD derived from the forecast sales with the following relationship:

$$\text{Annual MD}_{\text{MW}} = \text{Annual Sales}_{\text{MWh}} * (1 + \text{Loss Factor}) / (8760 * \text{ALF})$$

where:

Annual MD_{MW} : is the forecast Annual MD for the forecast year, in MW

Annual Sales_{MWh} : is the forecast Annual Sales for the forecast year, in MWh

Loss Factor : is the fraction of generated electricity lost in the transmission and distribution systems, typically 6% or 0.06 for Eskom.

ALF : is the Assumed Load Factor, for example 74% or 0.74

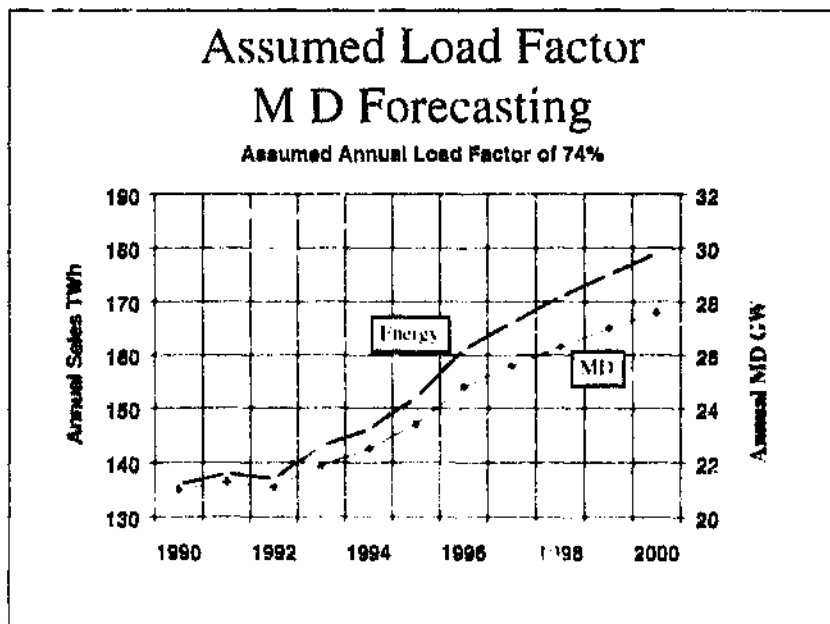


Figure 2.5. Assumed Load Factor MD Forecast

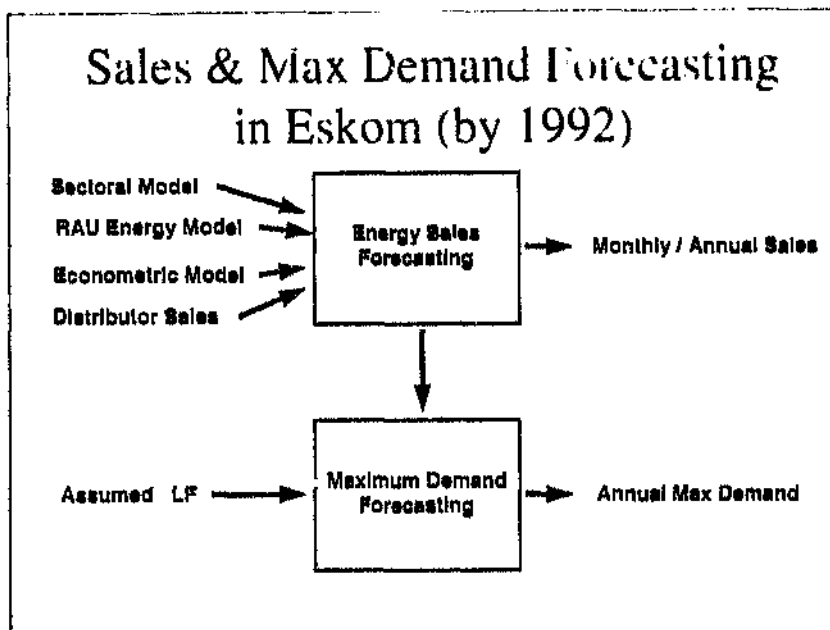


Figure 2.4 Eskom's Long Term Forecasting Process In 1992

A final energy sales forecast was derived from the output of several models and after consultation with experts both inside and outside the organization. (Typically, it was found that Eskom Regional Sales staff would under-forecast and Generation staff would over-estimate future sales.) The annual MDs were then derived from annual sales forecasts using an assumed load factor.

2.1.13 Berrisford 1993

The author, while studying the system demand profile to determine the impacts of Tariff E and the electrification program, became aware of the continued use of the Assumed Load Factor method of MD forecasting in Eskom. He identified several reasons for this method being inappropriate for Eskom in the future, including :

- The changing composition of Eskom's customer mix.
- A clear change in the trend of the system annual load factor.
- The introduction of DSM measures by Eskom.
- The impact of the national electrification program initiated in 1990.

The author briefly described several better methods of annual MD forecasting, and suggested that an hourly disaggregation approach with end-use aggregation models for specific customer classes be adopted. He then described a spreadsheet-based disaggregation model [Berrisford 1993b], based on class demand profiles from a previous disaggregation project [Bluff 1992a, b], and illustrated the ability of the model to identify suspected changes in the system demand profile.

2.1.11 Davison 1990

By the late '80s it was clear to Eskom forecasting staff that single line forecasts based on (previously) stable economic relationships were no longer adequate, and irrespective of new techniques, some means of including and dealing with increased uncertainty was essential. The message in the Commission's report (*understand global economic drivers*) was not lost on Eskom, as a paper on the use of scenario planning for forecasting [Davison 1990] illustrated. The scenario development was preceded by an evaluation of the process as used by other utilities, an analysis of the South African economic situation, and a detailed analysis of Eskom customer class attributes. This was followed by a look at environmental factors affecting the South African electricity market, including issues like urbanisation and the future prospects of South African gold in an increasingly competitive international market. Finally, four sets of congruent assumptions were developed as possible electricity sales scenarios, which were translated into quantified electricity sales forecasts. Annual MD were derived from these using the ALP technique. This project, carried out by Davison and Prinsloo, was the most comprehensive market research ever done for forecasting purposes, and added substantially to Eskom's understanding of the changing electricity sales environment.

2.1.12 Prinsloo 1992

During 1991 and 1992 Prinsloo developed a sectoral econometric model, forecasting over 60 sectors of electrical load separately [Prinsloo 1992]. Some of these sectors were individual large customers, while others were groups of smaller customers. Sales to each sector was forecast using a technique appropriate to that sector. Sales for traction, for example, were forecast using ton-km figures obtained from Spoornet. This model has since been improved and refined, currently consisting of over 90 sectors grouped by Standard Industrial Classification (SIC) code. This allows the sectoral energy sales forecast figures to be used directly in the XDEM demand profile forecasting model (see below).

By 1992 Eskom's long term forecasting process could be illustrated as in Figure 2.4. The scenario planning is not included, but formed an input in terms of assumptions used in the models. A long term econometric energy model (covering electricity, coal, and liquid fuels) developed by A. Gildenhuis in Eskom's Marketing Division, was used to 'quantify' the scenarios. Gildenhuis also developed a medium term electricity sales forecast model. The final energy forecast was then checked against national energy models, such as that by Kotze at the *Randse Afrikaanse Universiteit* [Kotze & Cooper 1985].

The author was unable to find additional evidence of improved forecasting methods in Eskom as a consequence of the CoE report. It does appear that broader consultation with external economics experts and customers was achieved.

To compound the forecaster's problems, the annual growth in 1984 was 8,8%, up from 2,4% in 1982 and 2,2% in 1983. This seemed to support the Norman view that the recent low growth was just a short term economic fluctuation. Nevertheless, the long term forecasts from 1983 to 1988 each showed successive reductions in long term growth rate (Figure 2.3), and by 1988 the forecast had assumed the new rate of about 5%.

1. 2. 3. 4. 5. 6. 7. 8. 9. 10. 11. 12. 13. 14. 15. 16. 17. 18. 19. 20. 21. 22. 23. 24. 25. 26. 27. 28. 29. 30. 31. 32. 33. 34. 35. 36. 37. 38. 39. 40. 41. 42. 43. 44. 45. 46. 47. 48. 49. 50. 51. 52. 53. 54. 55. 56. 57. 58. 59. 60. 61. 62. 63. 64. 65. 66. 67. 68. 69. 70. 71. 72. 73. 74. 75. 76. 77. 78. 79. 80. 81. 82. 83. 84. 85. 86. 87. 88. 89. 90. 91. 92. 93. 94. 95. 96. 97. 98. 99. 100. 101. 102. 103. 104. 105. 106. 107. 108. 109. 110. 111. 112. 113. 114. 115. 116. 117. 118. 119. 120. 121. 122. 123. 124. 125. 126. 127. 128. 129. 130. 131. 132. 133. 134. 135. 136. 137. 138. 139. 140. 141. 142. 143. 144. 145. 146. 147. 148. 149. 150. 151. 152. 153. 154. 155. 156. 157. 158. 159. 160. 161. 162. 163. 164. 165. 166. 167. 168. 169. 170. 171. 172. 173. 174. 175. 176. 177. 178. 179. 180. 181. 182. 183. 184. 185. 186. 187. 188. 189. 190. 191. 192. 193. 194. 195. 196. 197. 198. 199. 200. 201. 202. 203. 204. 205. 206. 207. 208. 209. 210. 211. 212. 213. 214. 215. 216. 217. 218. 219. 220. 221. 222. 223. 224. 225. 226. 227. 228. 229. 230. 231. 232. 233. 234. 235. 236. 237. 238. 239. 240. 241. 242. 243. 244. 245. 246. 247. 248. 249. 250. 251. 252. 253. 254. 255. 256. 257. 258. 259. 260. 261. 262. 263. 264. 265. 266. 267. 268. 269. 270. 271. 272. 273. 274. 275. 276. 277. 278. 279. 280. 281. 282. 283. 284. 285. 286. 287. 288. 289. 290. 291. 292. 293. 294. 295. 296. 297. 298. 299. 300. 301. 302. 303. 304. 305. 306. 307. 308. 309. 310. 311. 312. 313. 314. 315. 316. 317. 318. 319. 320. 321. 322. 323. 324. 325. 326. 327. 328. 329. 330. 331. 332. 333. 334. 335. 336. 337. 338. 339. 340. 341. 342. 343. 344. 345. 346. 347. 348. 349. 350. 351. 352. 353. 354. 355. 356. 357. 358. 359. 360. 361. 362. 363. 364. 365. 366. 367. 368. 369. 370. 371. 372. 373. 374. 375. 376. 377. 378. 379. 380. 381. 382. 383. 384. 385. 386. 387. 388. 389. 390. 391. 392. 393. 394. 395. 396. 397. 398. 399. 400. 401. 402. 403. 404. 405. 406. 407. 408. 409. 410. 411. 412. 413. 414. 415. 416. 417. 418. 419. 420. 421. 422. 423. 424. 425. 426. 427. 428. 429. 430. 431. 432. 433. 434. 435. 436. 437. 438. 439. 440. 441. 442. 443. 444. 445. 446. 447. 448. 449. 450. 451. 452. 453. 454. 455. 456. 457. 458. 459. 460. 461. 462. 463. 464. 465. 466. 467. 468. 469. 470. 471. 472. 473. 474. 475. 476. 477. 478. 479. 480. 481. 482. 483. 484. 485. 486. 487. 488. 489. 490. 491. 492. 493. 494. 495. 496. 497. 498. 499. 500. 501. 502. 503. 504. 505. 506. 507. 508. 509. 510. 511. 512. 513. 514. 515. 516. 517. 518. 519. 520. 521. 522. 523. 524. 525. 526. 527. 528. 529. 530. 531. 532. 533. 534. 535. 536. 537. 538. 539. 540. 541. 542. 543. 544. 545. 546. 547. 548. 549. 550. 551. 552. 553. 554. 555. 556. 557. 558. 559. 560. 561. 562. 563. 564. 565. 566. 567. 568. 569. 570. 571. 572. 573. 574. 575. 576. 577. 578. 579. 580. 581. 582. 583. 584. 585. 586. 587. 588. 589. 590. 591. 592. 593. 594. 595. 596. 597. 598. 599. 600. 601. 602. 603. 604. 605. 606. 607. 608. 609. 610. 611. 612. 613. 614. 615. 616. 617. 618. 619. 620. 621. 622. 623. 624. 625. 626. 627. 628. 629. 630. 631. 632. 633. 634. 635. 636. 637. 638. 639. 640. 641. 642. 643. 644. 645. 646. 647. 648. 649. 650. 651. 652. 653. 654. 655. 656. 657. 658. 659. 660. 661. 662. 663. 664. 665. 666. 667. 668. 669. 670. 671. 672. 673. 674. 675. 676. 677. 678. 679. 680. 681. 682. 683. 684. 685. 686. 687. 688. 689. 690. 691. 692. 693. 694. 695. 696. 697. 698. 699. 700. 701. 702. 703. 704. 705. 706. 707. 708. 709. 710. 711. 712. 713. 714. 715. 716. 717. 718. 719. 720. 721. 722. 723. 724. 725. 726. 727. 728. 729. 730. 731. 732. 733. 734. 735. 736. 737. 738. 739. 740. 741. 742. 743. 744. 745. 746. 747. 748. 749. 750. 751. 752. 753. 754. 755. 756. 757. 758. 759. 760. 761. 762. 763. 764. 765. 766. 767. 768. 769. 770. 771. 772. 773. 774. 775. 776. 777. 778. 779. 780. 781. 782. 783. 784. 785. 786. 787. 788. 789. 790. 791. 792. 793. 794. 795. 796. 797. 798. 799. 800. 801. 802. 803. 804. 805. 806. 807. 808. 809. 810. 811. 812. 813. 814. 815. 816. 817. 818. 819. 820. 821. 822. 823. 824. 825. 826. 827. 828. 829. 830. 831. 832. 833. 834. 835. 836. 837. 838. 839. 840. 841. 842. 843. 844. 845. 846. 847. 848. 849. 850. 851. 852. 853. 854. 855. 856. 857. 858. 859. 860. 861. 862. 863. 864. 865. 866. 867. 868. 869. 870. 871. 872. 873. 874. 875. 876. 877. 878. 879. 880. 881. 882. 883. 884. 885. 886. 887. 888. 889. 890. 891. 892. 893. 894. 895. 896. 897. 898. 899. 900. 901. 902. 903. 904. 905. 906. 907. 908. 909. 910. 911. 912. 913. 914. 915. 916. 917. 918. 919. 920. 921. 922. 923. 924. 925. 926. 927. 928. 929. 930. 931. 932. 933. 934. 935. 936. 937. 938. 939. 940. 941. 942. 943. 944. 945. 946. 947. 948. 949. 950. 951. 952. 953. 954. 955. 956. 957. 958. 959. 960. 961. 962. 963. 964. 965. 966. 967. 968. 969. 970. 971. 972. 973. 974. 975. 976. 977. 978. 979. 980. 981. 982. 983. 984. 985. 986. 987. 988. 989. 990. 991. 992. 993. 994. 995. 996. 997. 998. 999. 1000.

"The forecasting literature on the demand for electricity in South Africa consists of extrapolations, *naïve* regressions, and some attempts to use input-output models...The reviewed studies are criticised on the basis of the hypothesis on which their forecasts are developed. It is suggested that the studies suffer from spurious correlations, inadequate statistical investigation of the data and mainly restrictive specification of the model...It is suggested that research is needed in developing models to investigate price effects, energy/non-energy substitution, interfuel substitution and energy price-macro-economy feedbacks."

The author finds this criticism rather biased by the incredible gift of hindsight. Similar criticism in 1981 would have been ridiculed, as the simple models used by Eskom had performed remarkably well until that time - despite their theoretical imperfections. The failure of the forecast in 1982 was due to a lack of understanding of the local and international drivers of economic growth, and their consequences for electricity sales growth. This was illustrated by the De Villiers Commission, which in 1984 concluded that a structural change in energy economics had resulted in a permanent change in world economies following the 1973 oil crisis, which had finally caught up with South Africa in 1982. This, they wrote, implied a long term growth for future Eskom sales, of about 5% and not 7% as was then forecast by Eskom. Their forecast was made *without any model*, and was based only on a thorough understanding of global economic events. It was also more accurate than the Eskom forecast. Although the Commission did their study after the sales drop of 1982, it is clear that the data they used could have been used by Eskom to predict the drop. It is also clear, from internal memoranda, that certain people within Eskom, including Stoffberg, suspected the drop in sales was *structural and permanent* by 1983, but were unable to convince Eskom management of this. It must be borne in mind that Eskom had faced some critical capacity shortages during the winters in the late '70s. This had led to a 'Never again' attitude by management (to the possibility of capacity shortages), which resulted in a preference to err on the high side.

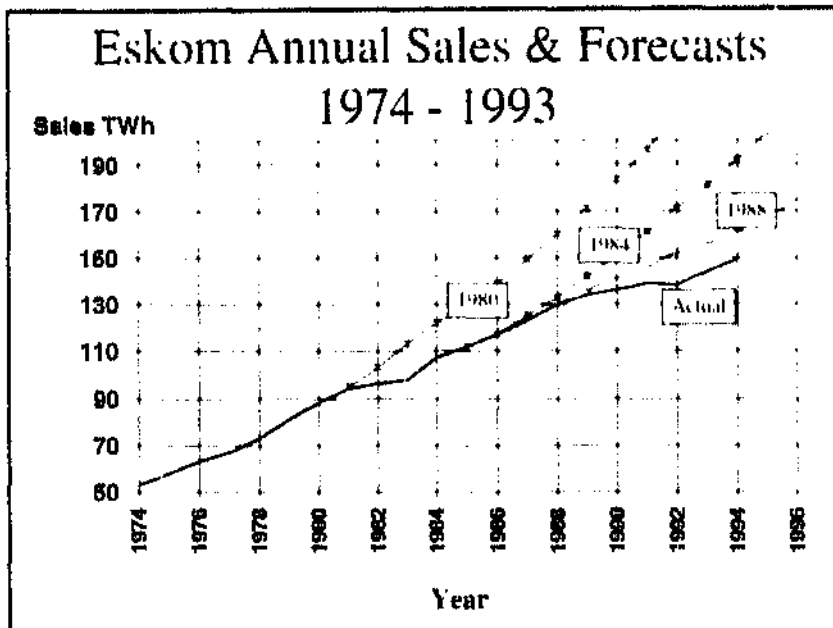


Figure 2.3 Eskom Annual Sales and Forecasts

An Eskom public information brochure dated April 1986 [Eskom 1986] describes Eskom's forecasting process as based on four 'independent methodologies', these being:

- **Customer Opinion Survey**, which involves interviews with Eskom's largest and potentially largest customers to obtain updates of their projected consumption.
- **Time Series Modelling**. This method uses an electricity sales model developed by an independent economic forecasting company, which analyses cyclic factors and underlying economic trends.
- **Sectoral Model**, which uses past statistics of electricity consumption and forecasts the future demand in five different sectors of the economy, these being Mining, Industry, Traction, Bulk (or Municipalities), and Domestic & Street Lighting. The model took into account GDP, inflation, exchange rates, industrial production, and relative prices of different energy forms.
- **Energy / GDP Model**. This was the Stoffberg/Norman model, which relied on the relationship between GDP growth and energy growth in the country.

The brochure then mentions that the above models are run for several different economic scenarios, i.e. GDP growth rates of 2.5%, 3.5%, and 4.5% in 1986. Forecasts were then modified to include the expected impacts of demand side management programs. It concludes by stating that Eskom is constantly examining methods of improving inputs to its load forecasting process.

R105 billion by the year 2005. The Commission made the following recommendations regarding long term forecasting:

- "The risks implied by load forecasts for electricity consumption which may present estimates of growth which could be too high or too low, should be reduced to a minimum.
- Close co-operation should be elicited from consumers when establishing future electricity consumption requirements.
- A power station construction programme should be developed which is based on the simultaneous construction of more than one power station, but which possesses sufficient flexibility in respect of follow up sets to allow the assimilation of changes in growth rate which require constant monitoring, without supplying an excess of generating capacity."

These recommendations are followed by this statement:

"Since 1973, the econometric method of forecasting electricity consumption has become unreliable, as a result of a discontinuity in the world's economic growth pattern."

2.1.10 Joubert G 1985

One consequence of the De Villiers Commission of Enquiry in 1984 [Col: 1984] was the study carried out by Joubert [Joubert 1985] to evaluate the use of Box-Jenkins (ARIMA) time series models as an alternative to the sectoral forecast. Joubert forecast the years 1970 - 1980, using monthly sales data for four sectors, and adding a year to the model data for each successive forecast year. The study indicated that no improvement on the sectoral approach could be achieved with uni-variate ARIMA models. A bi-variate model that used 'consumer expectations' as the independent variable was also tested, and indicated that under certain circumstances an improvement could be expected. It appears that this approach was subsequently abandoned. Joubert also attempted to derive price elasticity information from sales and tariff data, which yielded very low and somewhat uncertain elasticities associated with long time lags. The author is not convinced that changes in demand during that period were actually due to changes in electricity price, as suspected by Joubert.

camps within the organisation. It seems that Stoffberg felt that there were warnings of a possible *permanent structural* change in the historical relationship between the electricity growth rate and the GDP growth rate, and he appears to have supported a revised long term growth rate of about 5.6%. Norman, at the same time, felt that the 2.4% pa growth of 1982 was due to medium term economic cycle variations and not a structural change in the growth rate. He therefore supported a long term growth of about 7% pa.

An Eskom internal memorandum in April 1984 [Eskom 1984] (probably in response to queries by the De Villiers Commission of Enquiry) describes two forecasting approaches used. The 'econometric' method is that developed by Stoffberg and later used by Norman. Also described for the first time is the 'sectoral' forecast, which is an econometric model based on independent forecasts for five industrial 'sectors'. The memo explains lower sales (than expected) as a consequence of a change in the structure of the economy, moving away from energy intensive primary industry to more labour intensive manufacturing industry, and concludes :

"It is clear that Eskom should give continued attention to the development of its forecasting techniques. It would be wrong, however, to pretend that "whatever the sophistication of the methods, forecasting is ever likely to be a certain business.....This underlines the need to accept changes in medium and long term forecasts and the importance of flexibility in the expansion plans based on these forecasts."

2.1.9 Recommendations of the De Villiers Commission of Enquiry, October 1984

The large increase in the price of electricity in 1980 followed by another in 1984 focused public attention on Eskom, who needed the increased revenue to finance their expansion plan. This plan was based on the econometric forecasts which had served Eskom well until 1981, when the constant growth of about 8% per annum suddenly declined. The De Villiers Commission of Enquiry [CoE 1984] evaluated Eskom's past performance, with respect to Eskom's objective and policy of management, and against the performance of major electricity suppliers in other countries. The CoE found it necessary to consider two periods of time independently, namely 1950 to 1974 and 1974 to 1982. The CoE felt that the oil crisis of 1973 had produced a discontinuity in the world economy, which had repercussions for the global electricity supply industry. This had changed the previously stable relationships between GDP, energy, and electricity sales, disrupting the trends central to econometric forecasting models. South Africa was able to stave off the impact of this disruption for several years, till 1981, because of an abundance of local coal and large energy intensive industries. The Commission analysed international growth trends and South African statistics after 1973 in detail, and concluded that Eskom's sales growth was likely to be about 5% per annum. This was substantially lower than the official Eskom forecast predicting about 7%. The cost implications of this difference were reported to be

using GDP data for the period 1946 to 1975. This was essentially a simple **macro econometric model**. Norman then assumed a saturation of 75% for the electricity component of energy required in the country, and developed **logistic and modified Gompertz models** to predict electricity growth. He felt that the Gompertz model was more accurate and used that for his energy forecast. Norman then calculated annual MDs using assumed load factors of 77% for Eskom and 40% for Municipalities. With Eskom supplying 90% of the energy, this implies an overall system LF of 70%.

Norman's second forecast in 1982 was similar to the first, but updated energy sales and GDP data (1950 to 1980) gave slightly different coefficients for the models, and he opted for the logistic form of the saturation curve rather than the Gompertz model. He again used the ALF method of forecasting annual MD, using a national average LF of 74%.

2.1.8 The Sales Growth Discontinuity of 1982

1981 was the last year that proved a consistent exponential electricity sales growth pattern (see Figure 1.2). After decades of repeatable growth of about 8% per annum, the sales growth in 1982 dropped suddenly to 2.4%. This was initially considered to be a short term aberration, but the growth in 1983 was even lower, at 2.2%.

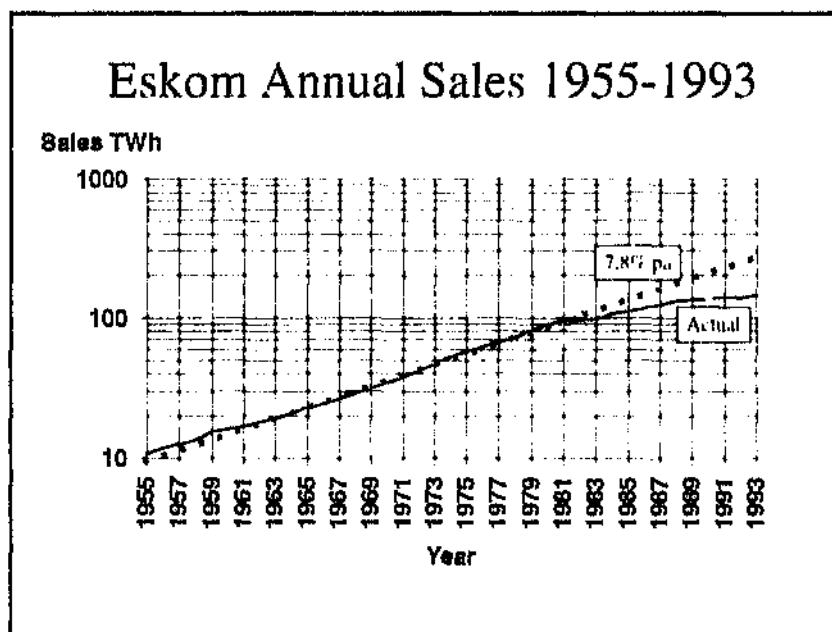


Figure 2.2 Eskom Annual Sales 1955 to 1993

By late 1983 doubts were being raised as to the accuracy of Eskom's long term forecasting process, leading to various internal documents querying and justifying the forecasts and explaining the growing differences between the forecasts and actual sales figures. Letters between managers in Eskom from 1983 and 1984 indicate two

- The forecast for total South African sales was based on an integration of the forecasts for each of eight Undertakings and five Municipalities. The **best fit functions** for each Undertaking were **combined in three different ways**, to produce three final aggregated annual energy sales forecasts.
- Joubert did not forecast maximum demands. He did, however, use a computer model developed by GEC to forecast **hourly demand profiles** for each Undertaking and the total sum. This model represented the annual demand profile as three daily profiles for each month. These were average Weekday, Saturday, and Sunday profiles. Forecast hourly profiles for 1980, based on 1970 profiles, were tabulated. Although Joubert recognised some of the advantages of demand profile forecasting as opposed to MD forecasting, he did not pursue this approach further.

2.1.6 Stoffberg 1975

Stoffberg in 1975 suggested that a stable linear relationship existed between South Africa's economic growth (as measured by the GDP) and the total energy consumed in the country [Pouris 1986]. Similarly, there existed a linear relationship between the total energy and the electrical energy consumed in the country. He expressed these relationships as follows:

$$Z = ax + by \quad (2.1)$$

where Z is the GDP, x represents the electricity component of total energy, and y represents the non-electrical energy contribution. The coefficients a and b he found by fitting the model to energy and GDP figures for South Africa, the USA and the UK, for the years 1947 to 1972. The relationship indicated a continued exponential growth in electricity sales. The electricity proportion of energy use in South Africa was increasing steadily, and Stoffberg assumed a saturation level of 75% by the year 2000.

2.1.7 Norman 1977 & 1982

Norman produced two forecasts, the first in 1977 [Norman 1977] and the second in 1982 [Norman 1982]. In 1977 Norman started with the Stoffberg energy/economy relationship:

$$Z = ax + by \quad (2.2)$$

He then developed a forecast of GDP with the exponential form:

$$Z = cd^t \quad (2.3)$$

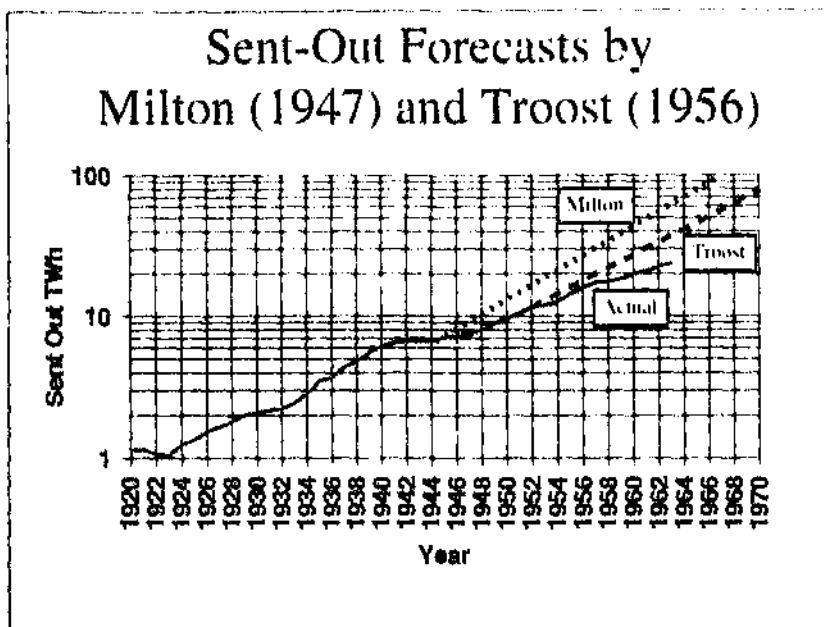


Figure 2.1 Forecasts by Milton and Troost

2.1.4 Straszacker 1966

The long term forecast by Straszacker [Straszacker 1966], was based on the technique used by Felix in 1964. Felix suggested that the major determinants of demand were the population in a country and estimates of electricity consumption per capita. Straszacker assumed a population growth for South Africa resulting in 37 million by the year 2000. He used a development growth in kWh per capita derived from the median of the 153 countries studied by Felix, but adapted to South African conditions with South African statistics for population and electricity consumption spanning 1917 to 1964. This resulted in a average long term electricity growth rate of 7.5% per annum. Although this proved fairly accurate, Straszacker's assumption of decreasing future load factor resulted in a poor forecast of capacity requirements.

2.1.5 Joubert J T 1971

Joubert, in his MBA dissertation [Joubert 1971], provided a thorough review of previous forecasts, and then introduced several new aspects in his forecast. These include:

- Joubert recognised that a single trend extrapolation function may not capture all the likely future developments. He applied eleven extrapolation functions to sales data for each Eskom Undertaking, the Eskom total and the South African total. These functions included **polynomials, exponentials, saturation curves, and averaging techniques**. The functions were tested for fit to the historical data and the best functions for each Undertaking were selected for the overall forecast

Chapter 2 - Demand Forecasting In Eskom

2.1 LONG TERM FORECASTING TECHNIQUES USED IN ESKOM

A look at the evolution of long term forecasting in Eskom will give some insight into the reasons for success of the relatively simple techniques used by in the past, as well as the reasons for their failure in recent years. The reader is referred to the reference documents if more details are required.

2.1.1 Milton 1947

The earliest record of a forecast in Eskom that the author could trace was that by Milton in 1947 [Milton 1947]. The technique he employed was simple **exponential extrapolation** of historical annual electricity sales figures. Milton applied an exponential electricity growth rate of about 11%, modified slightly to account for issues like the 'recovery' from the effect of the war years. He forecast annual MD by assuming a system annual load factor, which he expected to increase slowly at the rate of 0.1% per year.

2.1.2 Troost 1956

A forecast by Troost in 1956 [Troost 1956] assumed an exponential growth rate of 8%, and stated that "only a catastrophe can prevent a continual growth in demand for the next 20 years". Troost also used the ALF method, and assumed an improvement in annual LF from 67% in 1952 to 70% by 1970.

The Milton and Troost forecasts are illustrated in Figure 2.1, along with actual sent-out figures. Both forecasts were high.

2.1.3 Fenwick and Torr 1961

A forecast by Fenwick and Torr in 1961 [Fenwick & Torr 1961] mentions the influence of external factors like population and labour on the forecast, as well as the importance of forecasts of local demand in order to correctly site new generating plant. Although this forecast did not include MDs, it was the first to recognize that factors other than historical growth could influence future growth.

3.3.3 Data Available for the Disaggregation Project

Monthly billing figures, including billable energy consumed and maximum demand, were available for almost all the large customers. Since the primary goal was to determine the class coincident peak demands, which inevitably occurred during a winter weekday, only the average winter weekday was modelled.

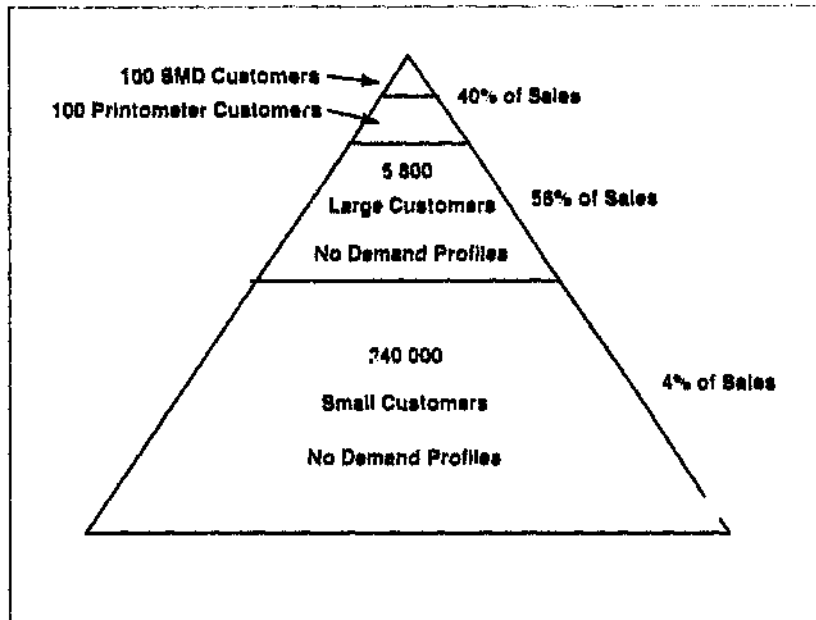


Figure 3.3 The Eskom Customer Pyramid in 1990

The billing records for June, July and August for all large customers therefore provided the customer population data. Demand profile data were available for 187 customers. As can be seen from Figure 3.3, these 187 customers represented almost 40% of Eskom's sales, even though they comprised only 3% of the number of customers.

3.4 CUSTOMER CLASSIFICATION

The Marketing Classification mentioned earlier, in which large customers form four classes (Mining, Industries, Bulk and Traction) and small customers form three classes (Domestic, Commercial, and Rural/Farming), was not entirely suitable for this project. The large customer classes were too coarse, and no demand profile data was available for any of the small customers.

similarities in daily demand profiles to reduce the quantity of data and filter out random variations.

The key problem was that it would not be possible to design representative samples of each customer class. We were required to carry out the project with existing demand profile data. This was limited to demand profiles used for billing purposes. A description of the tariffs and metering for billing purposes is necessary to appreciate the demand profile data set available.

3.3.1 The Electrical Load Structure

Eskom's customers are divided into two main groups, 'large' and 'small' customers. Large customers are those with notified demands in excess of 25kVA. Approximately 6 000 large customers consumed some 96% of total energy sales in 1990 and were supplied under a two-part energy and demand tariff, and recently also off-peak and Time-of-Use (TOU) tariffs. Some 240 000 'small' customers were on a variety of energy-only tariffs. Large customers comprised four classes, namely Mining, Industry, Traction, and Bulk. Bulk is a class of customers that redistribute power to most of the residential and commercial customers and manufacturing industry in the country. These include municipalities and other local authorities. The Mining and Industrial classes historically provided a dependable and consistent base load that comprised some two thirds of the system load. The 4% of sales to 'small' customers went to direct residential supplies, small businesses (commercial) as well as rural and farming customers. Figure 3.4 shows the sales per class for each of these seven classes in 1990.

2.3.2 Tariff Structures and Metering

The standard tariff for large customers (Tariff A) for many years has been a two-part energy and demand (Hopkinson) tariff, which encouraged customers to improve their load factors and limit their maximum demands. The mines and industries responded well to this message, typically achieving daily load factors in excess of 95%. Metering for the two-part tariff was simple and in most cases consisted of an energy meter with a thermal or block-interval (Metz) maximum demand indicator. The hourly (or half-hourly) demand figures from about 100 multiple point of supply customers were manually captured in each region every month. The data were transferred to a Head Office computer where the Simultaneous (or diversified) Maximum Demand (SMD) for each customer was calculated for billing purposes. This wealth of demand profile data was then discarded before the next billing date. A further 100 large customers with single points of supply were equipped with printometers for billing purposes. As a result, only about 200 of the 6 000 large customers had metering that is capable of providing demand profiles or suitable for more complex tariffs in 1990 (Figure 3.3). These printometer tapes for about 200 customers provided the bulk of the hourly demand data available in Eskom at the time. All the small customers use only single register kWh energy metering, also unsuitable for complex tariffs or load research purposes.

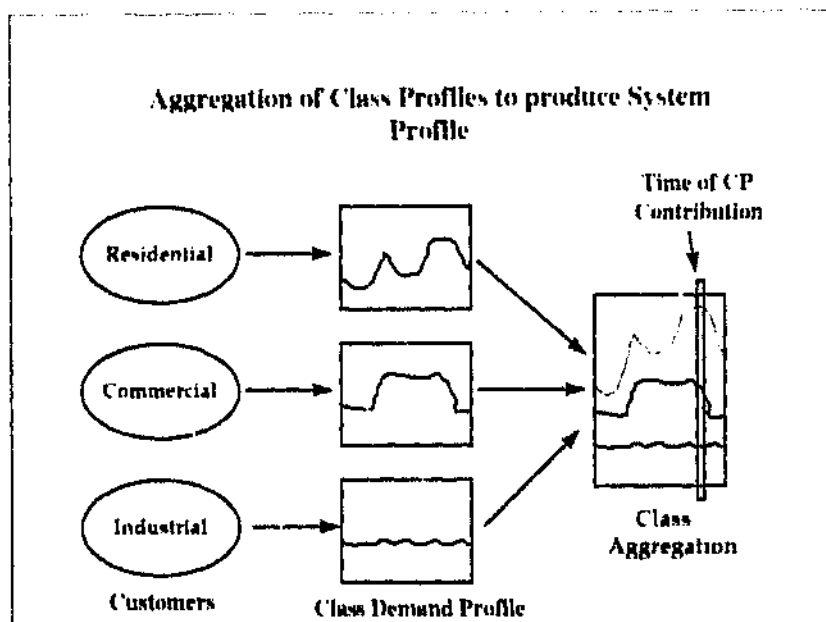


Figure 3.1 Class Aggregation Process

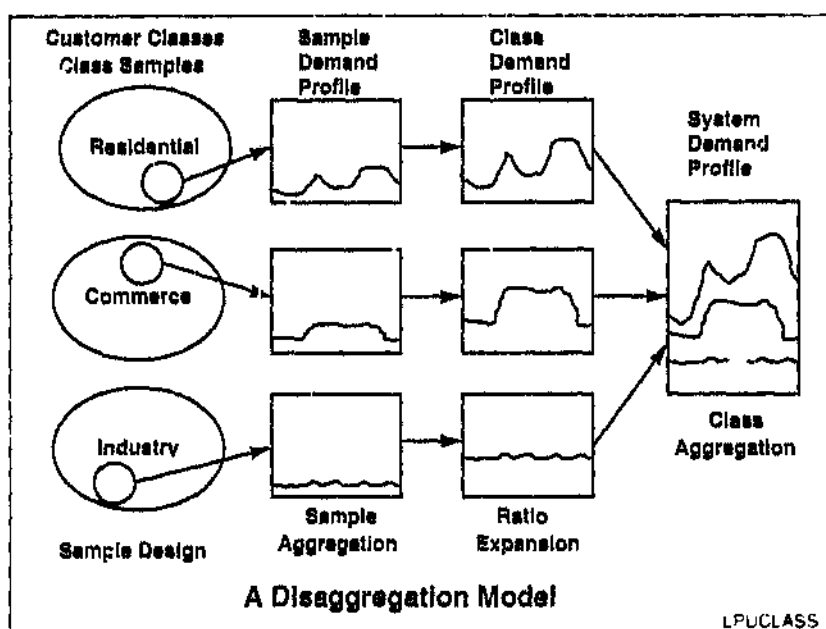


Figure 3.2 A Disaggregation Model

As it is also impractical to model each hour of the year, the model condenses the year into a number of day types for a number of seasons. This takes advantage of the

Chapter 3 - The System Disaggregation Project

3.1 INTRODUCTION

Although the Disaggregation Project is not part of this research project, it provided the data sets used in the XDFM model. As such the process, sample design, sample validation, and model testing have a direct bearing on the XDFM development. This chapter describes the Disaggregation Project [Bluff 1992a & b, Berrisford 1993a] to provide support for the development of the customer class demand profiles used later in the XDFM model. It must be noted that a lot of the work in this project was carried out by Ms E Bluff under the direction of the author.

Early in 1991 Load Research was requested to establish the contribution of various customer class to the system maximum demand. This was to form part of a cost-of-service study initiated by the Finance Department.

3.2 PROJECT OBJECTIVES

The purpose of this project was to determine the Coincident Peak (CP) contributions to the system demand of each of the major customer classes in the 'large customer' group. This information is used in the determination of tariff structures that reflect the costs of supplying different classes of customer. The basic process is shown in Figure 3.1. The large customer group contributes 96% of Eskom's revenue. A second objective was to determine the impact of Tariff E on the system demand profile if possible. A precision of 10% at the 90% confidence level was determined as a desirable target for each class CP contribution.

3.3 PROJECT OVERVIEW

It is impractical to obtain demand profiles for every large customer. The usual approach to determining customer class contributions would be to design a stratified random sample for each class, using standard sample design techniques. Demand profiles for each customer in each sample would be collected for the period of concern - in this case, a year. The average profile for each class would then be determined using mean-per-unit expansion or ratio expansion, and the classes then aggregated to model the system demand profile. The structure of the model is illustrated in Figure 2.2. The modelled system demand profile would then be tested against the actual system demand profile, available as the net output of all Eskom's power stations. If the correlation between the modelled and actual system profile is good enough, the CP contributions can then be derived from the class profile estimations.

2.3.3 The Goals of this Project

This research is aimed at providing Eskom with an alternative to ALF maximum demand forecasting, based on the principles of the best current practise by leading utilities. The alternative is intended to address the deficiencies in the current method subject to the constraints of Eskom's particular circumstances. The constraints include data availability and quality, financial limits, computing resources, and staff availability. These goals are illustrated below.

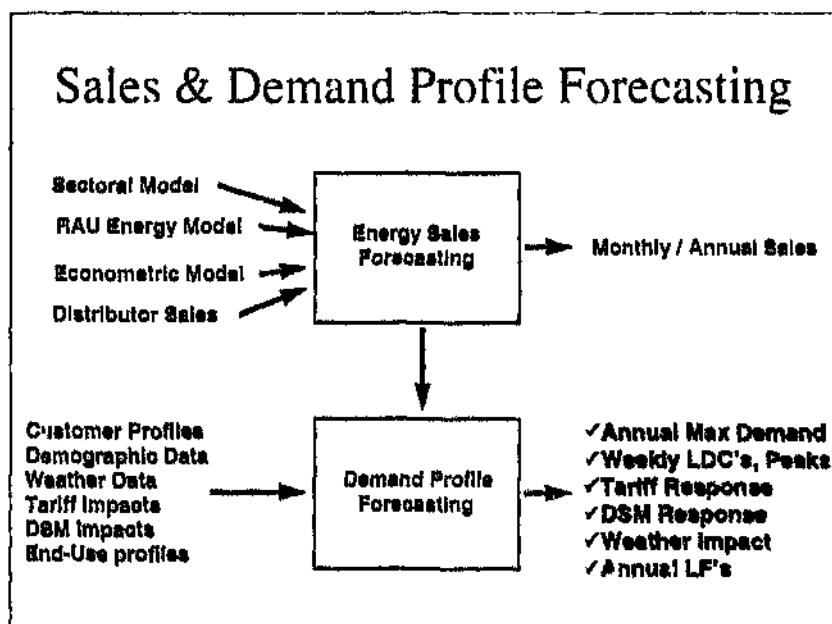


Figure 2.14 Proposed Long Term Forecasting Process

- Provision of weekly LDC's used for long term expansion planning
- System response to Tariff and DSM measures
- The impact of weather variations
- The impact of structural changes in the system load makeup

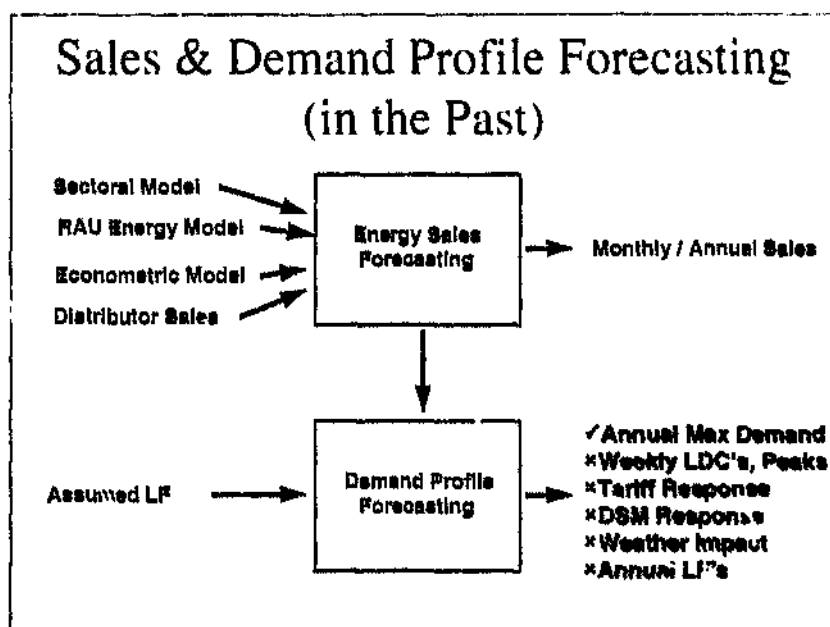


Figure 2.33 - Limits of assumed Load Factor Forecasting

Lastly, since an assumed LF is used in the forecasting process, the future system LF cannot be determined with this approach.

2.3.2 Conclusions

The above all indicates that there are serious shortcomings to the assumed load factor method of forecasting annual maximum demands. These can be summarised in the following two statements:

- The ALF method is no longer reliable and accurate, due to structural changes in the system demand profile.
- The ALF method cannot provide all the information necessary to plan future capacity in the most cost-effective manner.

2.2.4.4 Time-of-Use (TOU) Tariffs Proposed and Implemented

Interest in TOU tariffs and the related issue of marginal cost based electricity pricing grew, culminating in a report by the Pricing Policy Development Department in January 1989 [Calitz 1989]. This report recommended the introduction of TOU tariffs for large customers, using marginal costing as the basis for the tariff structure. TOU tariffs for large customers were introduced in 1990 as options, and formally promulgated as standard tariffs in 1995.

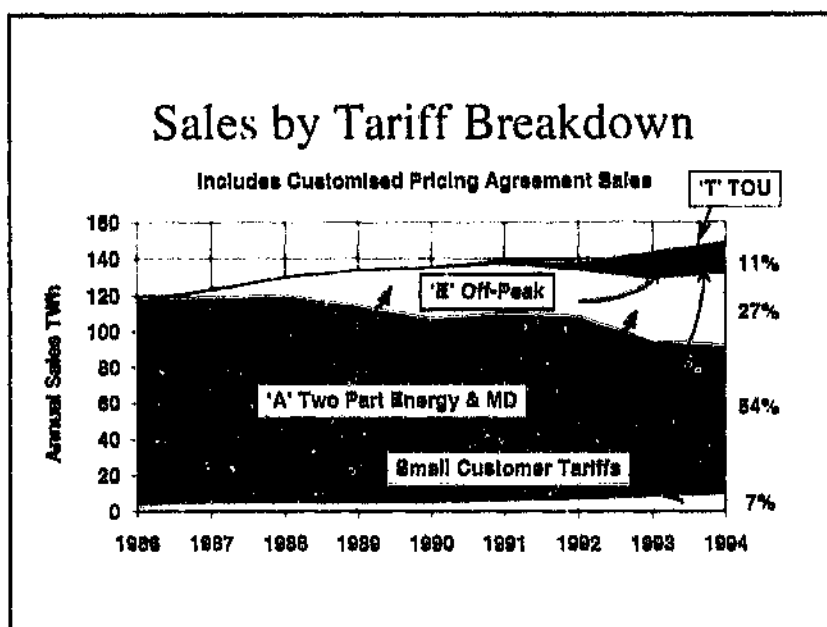


Figure 2.12 Migration of Electricity Sales Between Tariffs.

Eskom is also presently evaluating residential TOU tariffs for high consumption all-electric households. Figure 2.12 illustrates the migration of customers (and sales) from the standard two-part Hopkinson tariff to the off-peak and TOU tariffs. By the end of 1994, nearly 40% of Eskom's sales was billed on time-differentiated tariffs. These customers respond to the tariffs to varying degrees, altering the relationship between demand and energy consumption.

2.3. THE GOALS OF THIS RESEARCH PROJECT

2.3.1 The evaluation of the present process

The long term MD forecasting process used in Eskom was illustrated as Figure 2.4. The shortcomings of this approach have been discussed and are shown in Figure 2.13. These include the inability of the ALF method to deal with the following:

evening peaks, and after diversity load factors are in the order of 30%. These customers have made a contribution to the growing evening peak (Figure 2.8).

2.2.4.3 Tariff E - The first step into DSM

By the mid-Eighties it was apparent to Eskom that some form of DSM strategy had to be followed by the utility. In 1986 the first hesitant step in this direction was taken by introducing Tariff E. This was identical to the standard Tariff A but the customer's maximum demand was measured for billing purposes only during on-peak times (07h00 to 23h00, Monday to Friday, excluding Public Holidays). This was hesitant in that a 'safety net' was built into the tariff to limit the possible revenue loss to the utility. This limited the savings a customer could make to a maximum of 7% of his Tariff A bill. Some 200 large customers have opted for this tariff. Small process industries have been able to benefit most from Tariff E. Some of these customers have re-scheduled their plant operations to take full advantage of off-peak periods, both at night and during the weekends. Figure 2.11 shows the estimated average winter weekday demand profile of all industrial and mining customers in 1990. The average demand for these customers during peak hours was about 4 400 MW and during off-peak hours was about 4 700 MW. The reduction in average demand during peak hours is clearly evident, indicating load shifting of approximately 300 MW by Tariff E customers in these sectors.

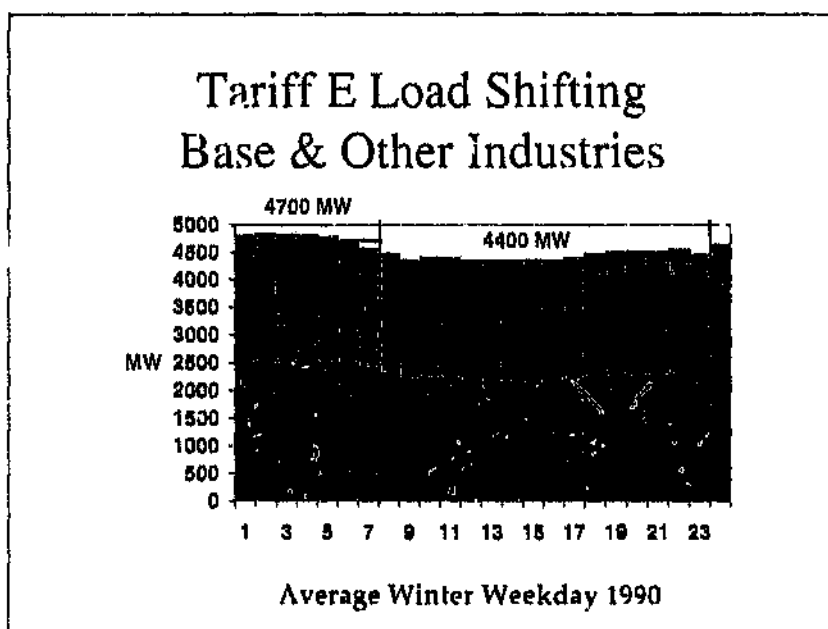


Figure 2.11 Load Shifting by Tariff E Customers

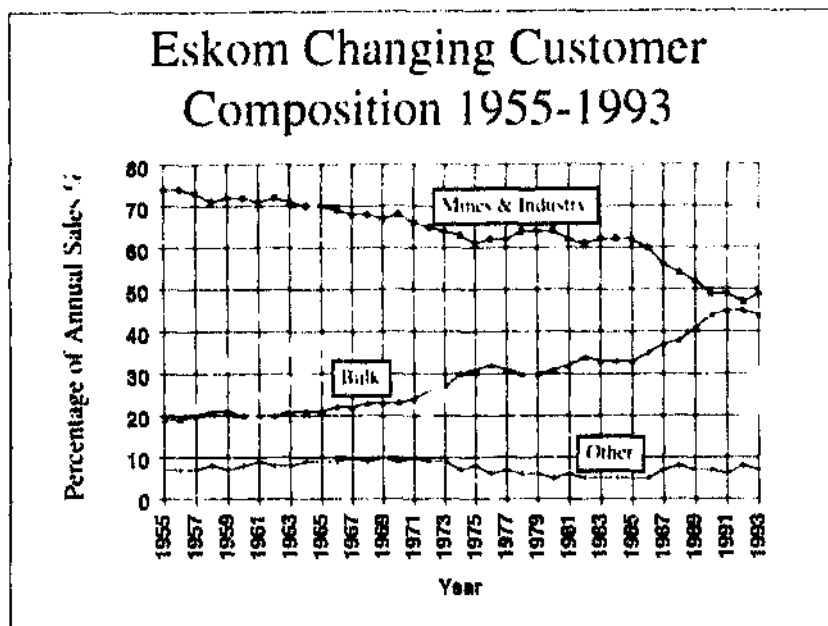


Figure 2.9. Eskom's Changing Customer Composition 1955 - 1993

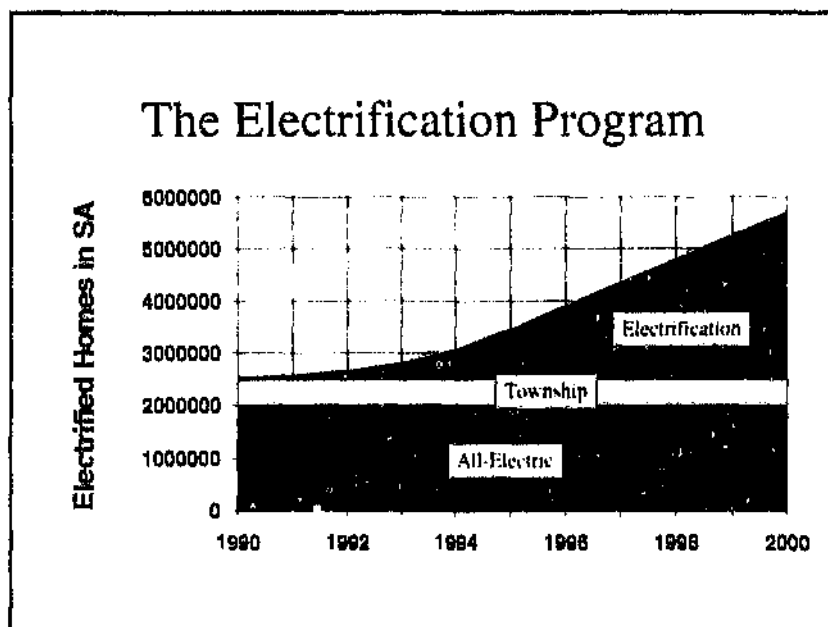


Figure 2.10 The Electrification Program

Nevertheless, the demand profiles of recently electrified customers are very peaky [Berrisford & Bluff 1991]. Their peaks are co-incident with Eskom's morning and

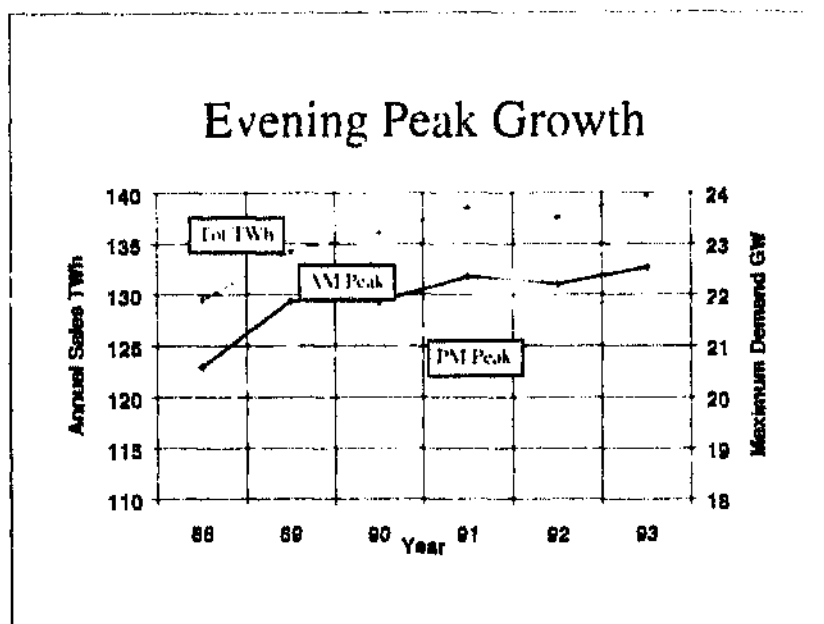


Figure 2.8 Evening Peak Growth

2.2.4 Factors Affecting the Structure of the Eskom Demand Profile

2.2.4.1 Changing Customer Composition

As can be seen in Figure 2.9, the Mining and Industrial sector contributions to the utility sales have declined from over 70% in 1960 to under 50% in recent years, while the Bulk supplies load has increased from 20% to over 40%. This is significant, as the load shape of the Bulk sector is peaky while that of Mining and Industrial loads is flat, and has contributed to the decline in the annual system load factor (see Figure 2.6). This change accelerated from 1985 to 1990, so that Bulk supplies now constitute about 45% of Eskom sales.

2.2.4.2 The National Electrification Program

In 1990 Eskom embarked on a country-wide program to provide electricity in the homes of all South Africans. This program, launched under the banner of "Electricity for All", aimed at electrifying over 3 million homes by the turn of the century. The plan will more than double the number of homes that were electrified in South Africa in 1990 (Figure 2.10). Initial estimates of the impact of this program on Eskom's system demand profile [Berrisford & Bluff 1991] have proved rather high, as the newly electrified customers consume less electricity (under 100 kWh per month) than expected (over 350 kWh per month).

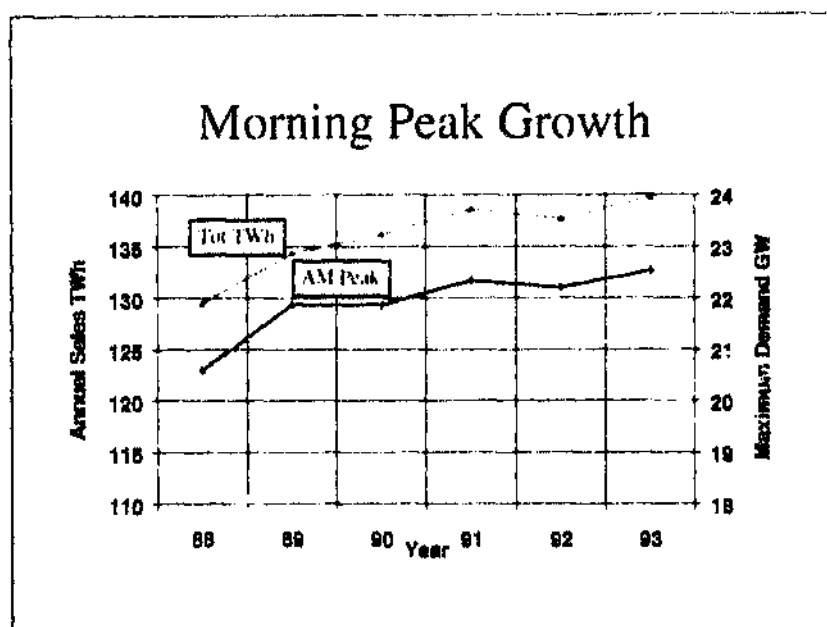


Figure 2.7 The Relationship between Morning Peak and Annual Sales

The relationship between the morning peak and the evening peak started changing after 1990, with the evening peak increasing in relative magnitude. The rising evening peak finally exceeded the morning peak in 1992 (see Figure 2.8), and since then the annual peak has occurred on a winter weekday evening at 19h00. The good relationship between sales and the morning peak is no longer of any significance, and the evening peak does not have the same relationship. The assumed load factor method can therefore no longer be accurately applied by Eskom.

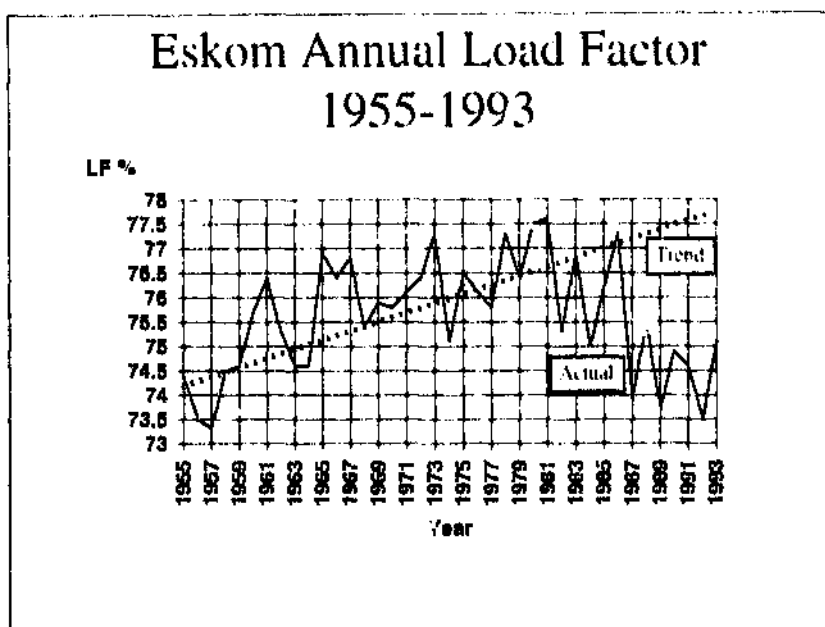


Figure 2.6. Eskom Annual Load Factor 1955 - 1993

The load factor is expected to deteriorate even further as a national electrification program takes shape [Berrisford & Bluff 1991]. Since 1980 the manufacturing and commercial load has also grown in magnitude, placing further pressure on the declining load factor. These customers are not supplied directly by Eskom, but indirectly via Bulk (Municipal) redistributors.

2.2.3 The Evening Peak Growth

Historically Eskom's annual peak demand occurred on a winter weekday morning, at 09h00. The peak in winter is due to increased heating demand in the colder weather, mainly in the all-electric residential sector and the commercial sector. The annual morning MD and annual sales are plotted below in Figure 2.7, for the period 1988 to 1993. The excellent correlation between sales and morning peak shows the inherent accuracy of the ALF method of annual MD forecasting during this period.

| Customer Class | Sample Size (Customers) | Error Ratio (MBSS) | Precision (MBSS) |
|------------------------|-------------------------|--------------------|------------------|
| Developing Communities | 11 | 0.144 | 7.1% |
| Bulk & Other | 25 | 0.144 | 4.7% |
| Traction | 27 | **** | **** |
| Other Industries | 15 | 0.0749 | 3.2% |
| Base Industries | 5 | 0.0669 | 4.9% |
| Other Mines | 9 | 0.1867 | 10.2% |
| Gold Mines | 40 | 0.0426 | 1.1% |

Table 3.7 - MBSS Precisions of Disaggregation Samples

The MBSS sample for Traction included all the customers, and no error ratio was calculated. The relative precision figures do assume that an optimally stratified MBSS sample is used, and an examination of the predetermined and MBSS samples revealed that at most all the predetermined sample customers were in the MBSS samples. The MBSS samples also included several smaller customers. These sample precisions are far more realistic. If weighted by class contribution proportions, they correlate well with the system level accuracy obtained with the model, as described later.

3.7 THE DISAGGREGATION MODEL IMPLEMENTATION

The demand estimation model for the system comprising seven classes is a three step averaging and summation process. The first step is to determine the average winter weekday (AWW) demand profile for each customer in each class sample. This was carried out for each of the 132 customers.

$$S_{ci}(t) = \frac{1}{d} \sum_{n=1}^d D_{cni}(t) \quad (3.4)$$

The second step involved creating the AWW profile for each sample by summing the individual customer profiles in each sample. The average winter weekday profile for each class was then produced by expanding the sample average winter weekday profiles using simple ratio expansion. The kWh energy consumption for the three winter months for both samples and populations were used as the ratio expansion variables. At this time the 5.3 % distribution system losses were proportionally allocated to each class.

$$K_i(t) = \sum_j S_{cij}(t) \cdot \frac{P_j}{Q} + 1.053 \quad (3.5)$$

As can be seen, Bsam5 was better with respect to the % contribution indicators, and Bsam4 was more accurate with respect to the weighted load factor. The customer contribution percentages were slightly suspect, as a customer considered to be a business in one municipality could be considered an industry in another. The WLF indicator was thus considered more important and Bsam4 was chosen as the most representative sample for the 'Bulk & Other' customer class.

A similar analysis of the 'Developing Community' sample revealed that no changes were necessary.

3.6.5 Testing of the Modelled System Demand Profile

Since doubts about a number of the samples existed, it was decided to test the final modelled system demand profile against the actual system profile for the average winter weekday before final acceptance of the predetermined samples. As will be seen, this test indicated a high degree of precision in the samples.

3.6.6 Sample Validation with DPFM Sample Design Error Ratios

Although no further sample validation was possible at the time of the project, the sample design carried out in 1994 for the DPFM project provided some statistical data that could be used to further validate the samples used in this project.

The DPFM samples were designed using MBSS methodology [Wright 1983, 1992]. A key component in MBSS sample design is the *error ratio* derived for each class from population consumption figures and the MBSS model. The relative precision for a given sample size is given by the following equation:

$$R = zC/\sqrt{n} \quad (3.3)$$

with:

- R is the relative precision
- z is 1.645 for a 90% confidence level
- C is the MBSS error ratio for the customer class
- n is the number of customers in the sample

The DPFM project used a totally new customer classification, based on SIC coding. This classification was designed in such a way that the 17 DPFM classes could be aggregated to the seven Disaggregation Project classes. The MBSS error ratios for each of the 17 classes were weighted by annual sales and combined to give error ratios for the seven classes in this project. Calculated relative precisions for the predetermined samples are tabulated below.

assess the reliability of these two samples, and if possible, to tailor them more accurately to the populations they represented. Average monthly load factor of Bulk customers appeared to be related to the small generic, cotile shape variations. The distribution of customer load factors was also much more normal than that of their consumption figures. The deviation of individual customer shapes is described by deviations of their average load factors. The *load factor* of the 'Bulk' customer, weighted by kWh consumption, is thus a more suitable variable for validating the shape of the 'Bulk' sample. The annual consumption breakdown for each 'Bulk' customer into domestic, commercial, industrial and other components was also available (Eskom 1990). The consumption components of both population and sample were determined. It was decided to tailor the 'Bulk' sample to represent the population as closely as possible with respect to weighted load factor (WLF) and consumption component ratios. These figures were used as indicators to determine sample validity. This process was carried out as follows:

a) The WLF and % contributions for both population (Bpop) and original sample (Bsam) were determined. These are listed in Table 3.6. As can be seen, the sample had a significantly higher WLF than the population, due to the higher industrial component.

b) The largest 'Bulk' customer (Durban Corporation) was in the sample. This customer consumed 13.7 % of the class usage, and had an unusually high load factor. When weighted by annual consumption, the contribution of this customer to the class weighted distribution was very high and biased the mean of the weighted distribution. It was removed from the sample.

c) Four of the sample customers (Johannesburg, Port Elizabeth, Cape Town and Bloemfontein) have their own generation capacity and one of them (Cape Town) also has a pumped storage scheme. This own-generation capacity is sometimes used for peak-opping their supply from the utility, which distorts their demand profiles. These four were also removed from the sample. The remaining sample (Bsam2) was a lot more like the population, but could still be improved.

d) Customers were successively removed from the sample and the indicators recalculated. For each iteration each of the remaining customers was evaluated. The customer having the most adverse impact on the indicators was then removed. This process is illustrated in Table 3.6.

| Sample | Weighted L.F | % Res | % Com | % Ind | % Oth |
|--------|--------------|--------|--------|--------|--------|
| Bpop | 65.99% | 33.59% | 10.44% | 44.90% | 9.07% |
| Bsam | 69.06% | 31.25% | 8.53% | 51.75% | 8.77% |
| Bsam2 | 67.19% | 33.05% | 8.87% | 49.48% | 8.58% |
| Bsam3 | 66.82% | 34.60% | 7.69% | 48.34% | 9.37% |
| Bsam4 | 66.08% | 35.02% | 8.19% | 47.03% | 9.76% |
| Bsam5 | 65.45% | 36.00% | 8.38% | 45.31% | 10.31% |

Table 3.6: Bulk Sample Adjustment

- **Other Industries :** This is the largest class in terms of number of customers. The sample is the poorest both in terms of numbers and percentage of class sales. Although redeemed to some extent by good demand management by the customers, and by small seasonal variations, it was considered poor.
- **Traction :** This sample consisted of 84 % of the customers and over 80 % of the annual consumption in the class. This sample was considered good.
- **Bulk and Other :** This and Developing Communities, (which is actually a subset of 'Bulk') are the only two classes unable to respond well to tariff messages. These are therefore most important when considering contributions to the system peaks. Several of the largest customers in the sample were known to be atypical of the class. Due to this, the 1000:1 consumption range, and logarithmic skew in the consumption distribution in the population, the sample could not be considered acceptable.
- **Developing Communities :** As with Bulk, there was a large variation in annual consumption figures and severe skew. Our sample was totally urban in nature, and we knew very little about rural village characteristics. It was felt that this sample required a closer look before it could be considered acceptable.

3.6.4 Further Validation of the 'Bulk & Other' and 'Developing Community' Classes

Due to the importance of these classes to peak contributions, it was necessary to find a means of validating these two samples despite the bias, skew and range problems. The standard sample design and sample validation techniques as used above, were developed largely around the needs of residential surveys at household level.

Though such populations can have consumption ranges of up to 30:1 and also exhibit skewed distributions, these are not as serious as those encountered in this project. The top ten Bulk customers consumed over 48% of class annual sales, and the largest was over 1 000 times the size of the smallest. As with the other class, the sample consisted of the largest customers. The sample size and their large customer bias could not be improved, but more suitable sample evaluation tests could be investigated. These had to take into account the distributions of the populations and had to be based on variables that better expressed the contribution of a customer to the class profile. What was really desired was to test the representativeness of the average weekday demand *shape* of the sample to that of the population. Variations in annual consumption were not the real issue, variations in demand profile *shapes* were. Bulk customers have a common or generic demand profile shape. This shape is unaffected by the customer's size - whether 1 MW or 1000 MW. All have morning and evening peaks coincident with the Eskom system peaks. The relative magnitudes of the two peaks and two valleys are a function of the residential/commercial/industrial load mix within the redistributor. More industry means more off-peak load. More residential load means sharper peaks. The concept of a *generic* load shape applies to only two classes - 'Bulk & Other' and 'Developing Communities', and to a lesser extent to certain Mining sub-classes. The author decided to use this property to more accurately

sample that represents the mean and variation (or diversity) of the variable of interest in the population. This is the approach to be used if expansion of the sample demand profile is to be done using MPU expansion. The precision of a MPU estimate depends on the variation of demand in the sample (or stratum for stratified samples). With ratio expansion, however, the mean or average customer is of no relevance whatsoever. The sample is required to represent only the total class demand. When the population is severely skewed, as is the case with electricity consumption, the mean customer demand has even less significance. The precision of a ratio estimate depends on the variance of the residual component of demand (i.e. the difference between each customer's demand and the demand that would be predicted based on the customer's consumption - which is the ratio estimate) [Wright 1992].

3.6.3 Subjective Sample Validation

Additional information that could be deduced from the billing figures included load factors, load factor variations, seasonal variations and non-seasonal variations, as well as consumption and load factor distributions. This permitted a series of subjective sample validation tests. When considered, these implied greater confidence in some of the samples than the initial statistical tests indicated. This applied in particular to the 'Bulk' and 'Developing Community' classes. These subjective tests, by their nature, are vaguely defined and unscientific, but nevertheless indicated that a careful analysis of the class and sample attributes could prove them more representative than the above statistical validation implied.

At this point the Load Research team had the following impressions about each of the class samples:

- **Gold Mines** : Demand profile data for 40 of the 93 gold mines, representing 70 % of the class consumption, was available. The mines all used some form of demand management in response to the high demand charge in Tariff A, resulting in excellent load factors. The larger mines were better at this, with daily load factors consistently in excess of 95 %. The seasonal variation in consumption was under 5 % from summer to winter. Five customers had opted for Tariff E. These were all in the sample, and no intentional response to this off-peak tariff was discernible. This sample was considered good.
- **Other Mines** : The sample was very small, although it represented 40 % of consumption. As with gold mines, load factors were very good and seasonal consumption variations were under 5 %. Several of these mines were on Tariff E and had shifted load to off-peak times, but they comprised an insignificant proportion of the class. This sample was considered satisfactory.
- **Base Industries** : The tiny sample of 5 customers was too small. These five were the base industries on Tariff E, and unfortunately no Tariff A customers were included. They represented about 25 % of the class consumption as well as 45 % of the class Tariff E sales. Since this is the class with the largest Tariff E load, this was important. As with the other base load classes, most of the customers had good load factors. This sample was provisionally accepted as adequate.

| Customer Class | Population Size
(Customers) | Sample Size
(Customers) | Precision
(SRS
Sample) |
|------------------------|--------------------------------|----------------------------|------------------------------|
| Developing Communities | 106 | 11 | 32.0% |
| Bulk & Other | 567 | 25 | 35.6% |
| Traction | 32 | 27 | 8.4% |
| Other Industries | 2442 | 15 | **** |
| Base Industries | 223 | 5 | **** |
| Other Mines | 409 | 9 | 64.9% |
| Gold Mines | 93 | 40 | 14.6% |

Table 3.5 - Predetermined Sample Precisions

The implication of the above validation is that the samples are not representative of their populations at the 90% confidence intervals (with the exception of Traction).

The SRS sample design and validation procedures were clearly not of much assistance in establishing confidence in the predetermined samples. The intuitive feelings of the project team, however, were that the samples were more reliable than the tests indicated. The author feels that there are several reasons that these sample design principles and validation tests do not apply to this project. The samples do not reliably represent the average customer in each class, or capture the diversity of demand in each population. The real issue is neither of these, but "Does the diversified demand profile of the sample represent the demand profile of the class?"

3.6.2.1 The 'Random' Aspect

Statisticians appear to have an almost religious reverence for the concept of randomly selected samples. This is in order to remove any bias a researcher might introduce by selecting a sample by some other means. Conventional sample design theory is built around the Central Limit Theorem (CLT), which states that the means of a large number of *random* samples for a population will tend to have a normal distribution with a mean equal to the mean of the population. [Cochran 1977, Frank & Althoen 1994]. When it is not possible to check the validity of a sample, the researcher is totally dependant on the properties of the CLT. This would occur when, for example, sampling the population to find the average weight of adults in the country. In most load research applications, statistical measures for the sample selected can be tested against those of the population, to confirm that the sample does indeed represent the population. A sample that proves to be non-representative can be discarded and another drawn - despite that fact that the original sample is statistically valid. The randomness is not as crucial in load research as in the social sciences.

3.6.2.2 The MPU Focus of Standard Sample Validation Tests

The SRS procedure and validation tests were derived from standard research sampling techniques [Cochran 1977], where the primary goal of the sample design is to obtain a

Normally, once a sample has been designed and selected, it will be validated by comparing several characteristics of the sample to those of the population, such as the means and standard deviations of the variable of interest.

3.6.1 Testing Validity as Simple Random Samples for MPU Expansion

The means and standard deviations in annual energy sales per customer for each class population and sample were determined. About 2% of the 'Bulk' and 'Developing Community' customers were excluded from their populations due to unreliable billing information. As expected (Figure 3.4), the sample means were greater than the population means, reflecting the fact that only the larger customers were present in the samples. The high standard deviations of the populations indicate the severe skew.

| Customer Class | Mean (Pop.) | Mean (Sample) | Std. Dev. (Pop) | Std. Dev. (Sample) |
|------------------------|-------------|---------------|-----------------|--------------------|
| Developing Communities | 418 | 559 | 269 | 95 |
| Bulk & Other | 2394 | 3549 | 2583 | 455 |
| Traction | 124 | 128 | 33 | 30 |
| Other Industries | **** | **** | **** | **** |
| Base Industries | **** | **** | **** | **** |
| Other Mines | 271 | 326 | 320 | 264 |
| Gold Mines | 978 | 1085 | 547 | 440 |

Table 3.4 - Population and Sample Characteristics

If the predetermined samples had been SRS samples, the expected precisions of each for a 90% confidence interval, are tabulated in Table 2.5. These calculations were made using the following equation:

$$R = \frac{k \cdot \sigma / \sqrt{n}}{\mu} \quad (3.2)$$

where:

- R is the relative precision
- k is 1.645 for a 90% confidence level
- σ is the population standard deviation
- n is the number of customers in the sample
- μ is the population mean

Although this Predetermined Sample Design was unacceptable from a SRS point of view, it was limited by the only customer demand profile data available at the time.

SRS leads to excessive sample sizes where the population distribution deviates significantly from Normal (or Gaussian). Statistical tests indicate that all the class populations (with the exception of Traction) are severely skewed to the right. This reflects the fact that there are many customers with relatively low annual consumption, with fewer having higher consumptions. This skewness is characteristic in utilities world-wide, and because of this SRS is not often used by load research practitioners [Wright 1993].

| Customer Class | Population Size
(Customers) | Sample Size
(Customers) | Sample Size
(SRS Sample) |
|------------------------|--------------------------------|----------------------------|-----------------------------|
| Developing Communities | 106 | 11 | 55 |
| Bulk & Other | 567 | 25 | 203 |
| Traction | 32 | 27 | 12 |
| Other Industries | 2442 | 15 | **** |
| Base Industries | 223 | 5 | **** |
| Other Mines | 499 | 9 | 216 |
| Gold Mines | 93 | 40 | 44 |

Table 3.3 - Population and SRS Sample Size

In practise, stratified random sampling [AEIC 1990a, Hines 1993] or Model Based Statistical Sampling (MBSS) [AEIC 1990a, Wright 1993] would be used, which would reduce the sample sizes indicated with SRS considerably. Stratified sampling is used where the population is known to consist of two or more distinct groups, or where the population distribution is known to be severely skewed. SRS and stratified sampling can be used with both mean-per-unit (MPU) expansion or ratio expansion. MBSS, which uses a model to make explicit use of the severe skew typically found in load research populations, can only be used with ratio expansion.

This exercise demonstrated only that the predetermined samples could not be considered as representative if a SRS approach had been followed. Significant sample size reductions could be achieved by stratified sampling, but this would have involved a lot of effort and the predetermined samples would have constituted only the upper strata. Stratified sample design was not attempted.

3.6 SAMPLE VALIDATION

Since designing or choosing the samples for each class was not possible, it was crucial that each sample was evaluated to determine how representative it was of it's class. The billing records provided monthly energy and maximum demand figures for each customer. Energy sales is the most commonly used proxy variable for sample design and validation in load research.

| Customer Class | Population Size (Customers) | Sample Size (Customers) | Sample Sales Contribution |
|------------------------|-----------------------------|-------------------------|---------------------------|
| Developing Communities | 106 | 11 | 40% |
| Bulk & Other | 567 | 25 | 30% |
| Traction | 32 | 27 | 80% |
| Other Industries | 2442 | 15 | 10% |
| Base Industries | 223 | 5 | 25% |
| Other Mines | 499 | 9 | 40% |
| Gold Mines | 93 | 40 | 70% |

Table 3.2 Population and Sample Sizes

It is clear that even though the numbers of sample customers are small relative to the population sizes, these samples contribute a considerable portion of the total sales. In order to get a 'feel' for appropriate sample sizes, it was decided to design samples and compare the predetermined and designed samples.

3.5.1 A Sample Design Exercise

As an exercise, sample sizes using a simple random sampling (SRS) approach were determined [Berrisford 1993a]. The SRS sample sizes (n_0) were reduced by applying a Finite Population Size (FPS) correction, as the actual populations were considerably smaller than the theoretical 'infinite population' assumed. Incomplete billing data for the population prevented this exercise for the two industrial classes. The equations used [AEIC 1974, 1990a] were:

$$n_0 = \frac{k^2 \sigma^2}{S_x^2} \quad , \quad S_x^2 = D^2 A^2 \quad , \quad \text{and} \quad n = \frac{n_0}{1 + n_0 / N} \quad (3.1)$$

where :

- k is 1.645 for 90% confidence level
- n_0 is the initial sample size
- n is the final sample size after FPS
- D is 0.1 for the 10% sample precision required
- x is the mean weighted annual consumption of the population
- N is the population size
- σ is the standard deviation of the weighted annual consumption of the population

As can be seen in Table 3.3, six of the seven samples are smaller than rule of thumb minimum size of 30. One of the predetermined samples (Traction) is larger than the required simple random sample size. Since the samples comprise the largest customers in each class, they actually represent large proportions of the class sales.

| Customer Class | 1990 Sales GWh | 1990 Sales % of Total |
|--------------------------------|----------------|-----------------------|
| Bulk : | | |
| --- Municipalities | 55 128 | 40.5% |
| --- Developing Communities | 3 947 | 2.9% |
| Mining : | | |
| --- Gold | 24 033 | 17.6% |
| --- Other | 9 330 | 6.9% |
| Industries : | | |
| --- Base | 19 441 | 12.8% |
| --- Other | 18 693 | 12.3% |
| Traction : | 3 958 | 2.9% |
| Other : | | |
| --- Domestic / Street Lighting | 1 081 | 0.8% |
| --- Commercial | 340 | 0.2% |
| --- Rural / Farming | 3 641 | 2.7% |
| --- Own Usage | 544 | 0.4% |
| TOTAL SALES | 140 136 | 100.0% |
| System Losses | (7 199) | (5.3%) |

Table 3.1 : Sales to Customer Class in 1990

3.5 THE SAMPLES

The available demand profile data for the 187 customers yielded good data for the three winter months for only 132 customers. These 132 customers consumed 36% of Eskom's sales. From billing records each of the 6 000 odd large customers was allocated to one of the seven revised class. Approximately 2 000 of these were relatively small commercial and farming customers in the 25 kVA to 100 kVA range billed on Tariff A, and these were included in the 'Other' class. About 150 customers were supplied under Tariff E, and these will be discussed separately. Table 3.2 lists the population and sample numbers for each of the seven classes. Note that the 2 000 small Tariff A customers and the 240 000 Tariff B, C, and D customers have not been included in the Bulk & Other population size count.

- All the small customers (direct residential supplies, commercial, rural and farm supplies) are grouped together as 'Other'. They contribute less than 5 % of the energy sales. Since these customers were expected to be similar to the residential and commercial customers supplied by the redistributors, and no demand profiles for them were available, they were lumped together with the remaining Bulk customers to form a new class, 'Bulk and Other'. The 0.4% for the utility own usage was added to the Bulk & Other class. System losses were proportionally allocated to each class (e.g. 2.9% of the system losses were added to the total kWh of the Traction class) during the class ratio estimation process. Table 3.1 shows the annual sales for these class in 1990, and Figure 3.5 illustrates the classification developed from the original Marketing classification.

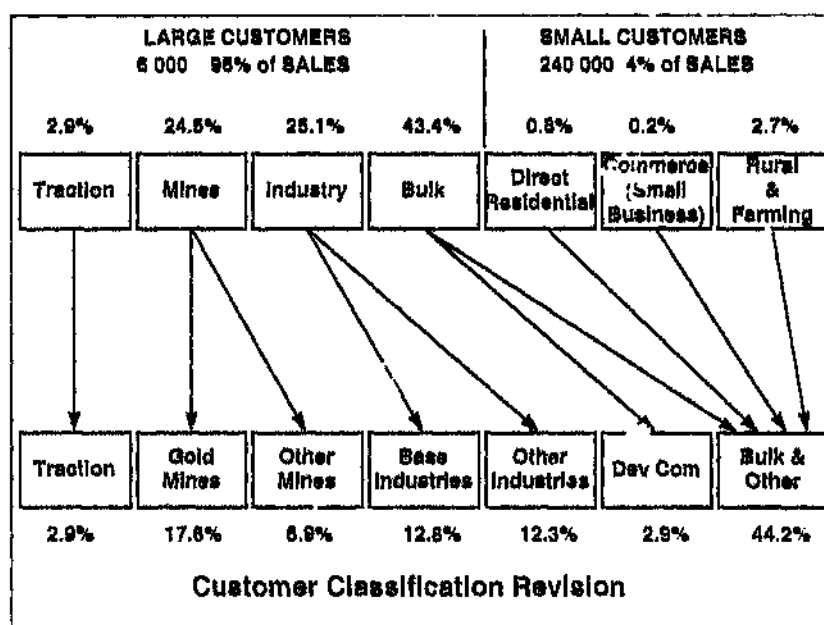


Figure 3.5 Revised Customer Classification

| Marketing's Customer Classification 1990 | | | | | | |
|---|-----------------|-----------------|-----------------|--|---------------------------|-----------------|
| Large Customers
8 000 96% of SALES | | | | Small Customers
240 000 4% of SALES | | |
| 2.9% | 24.5% | 25.1% | 43.4% | 0.5% | 0.2% | 2.7% |
| Traction | Mines | Industry | Bulk | Direct Residential | Commerce (Small Business) | Rural & Farming |
| Tariffs A, E, F | Tariffs A, E, F | Tariffs A, E, F | Tariffs A, E, F | Tariff C | Tariff B | Tariff D |
| <ul style="list-style-type: none"> ● Large Customer Classes too Coarse (ie Mines, Industry, & Bulk) ● No data were available for any Small Customer Classes ● There is no tariff differentiation in the Large Customer Classes | | | | | | |

Figure 3.4 Marketing Customer Classification

Unfortunately a radical departure from this classification would have rendered any analysis useless to the Marketing Department. The classification was therefore modified by splitting and regrouping the original classes into new classes. The following changes were made :

- Base Industries (primary metal ore processing and smelting) made up half of the Industrial sales. Due to the different nature of base industries to secondary or manufacturing industries, Base Industries were considered to be a separate class.
- Gold mines constitute over 70% of the Mining sales, and are collectively subject to independent load variations due to exchange rate and gold price changes. Mines were therefore divided into Gold Mines and Other Mines.
- The Bulk class includes Municipalities and Developing Communities as well as supplies to neighbouring countries. Developing Communities are residential communities that have traditionally used alternative domestic fuels (wood, coal, paraffin etc.). These communities have recently been electrified and are now developing the use of electricity as a residential fuel. They are characterized by a very high residential component (>>80%) with a low load factor (30%-50% Weekly L.F). Developing Communities are the most important growth sector due to the national electrification program currently underway. Because of the high growth potential and low load factor of these customers, they were considered as a separate class.

In order to test this concept, the author developed an aggregation model. This was based on the limited demand profile data used to successfully disaggregate the system winter weekday of 1990. The model could be tested by forecasting 1991 and 1992 demand profiles and testing the forecast against the actual demand profiles for these years. The goal was to determine if a demand profile model could discern the impacts of the above influences or not.

4.1.6 A Note on Confusing Terminology

The use of the terms aggregation and disaggregation may be very confusing. The difference between the two is subtle, but important. It has more to do with the objective than the structure of the model itself. Disaggregation refers to the process of breaking the system profile into its constituent components, using the system profile as the reference. Aggregation is the process of constructing the system demand profile from its constituent components. In this case the end-use profiles are the references. This may seem like splitting hairs, but it becomes relevant here. The *disaggregation* carried out for 1990 provided a set of class demand profile shapes that represented the system. These demand profile shapes can be weighted by expected future class sales figures and *aggregated* to produce a forecast system demand profile. Thus similar data sets and model structures can be both aggregation and disaggregation models, distinguished primarily by the approach and application of the model.

4.2 REPRESENTING THE ESKOM SYSTEM DEMAND PROFILE

Models of utility demand profiles usually use a summarised version of the annual demand profile [Gellings & Taylor 1981, Dickson 1984, EPRI 1985a, Gellings 1991], as it is impractical to model all 8 760 hours per year. The annual demand profile is represented as a number of shorter 'typical' periods. Where the profiles of weekdays and weekends differ, an average weekday and an average weekend day profile may be used. Where seasonal variations are significant, these may be duplicated for each season. The selection of the appropriate representation is a function of the utility profile and a compromise between complexity and inaccuracy in the model.

4.2.1 The Representation of System Demand Profile for the Disaggregation Model

For the 1990 disaggregation project, the system Average Winter Weekday (AWW) had been modelled. There were several reasons for this, including :

- Eskom is a winter peaking utility. The system demand during winter is therefore of most importance. The disaggregation team chose the billing months of June, July and August to be winter, as billed sales for these months were higher than in the other months of 1990 (Figure 4.1).

Two techniques for end-use forecasting have emerged. The first is a theoretical engineering approach called **thermal load modelling**, in which detailed data on weather, thermal characteristics of buildings, and appliance loads are modelled on a theoretical basis. A simple form of this type of end-use model has been developed by Eskom's Pricing Policy Department [Probert 1992] to study residential DSM options.

The second is a statistical approach, where end-use demand profiles are estimated from actual observed data. This can be derived from samples of metered end-use profiles or statistical analysis of customer level profiles and end-use application information using a technique known as **Conditional Demand Analysis (CDA)** [Parti & Parti 1980]. Load Research had developed a CDA analysis of several hundred household level profiles from Naledi in Soweto in 1993 [Nyikos et al 1994], and the technique appears to work well.

A third approach, which combines the above two techniques, was developed by EPRI in 1985 [EPRI 1985]. This method, known as the **Statistically Adjusted Engineering (SAE)** approach to end-use modelling, combines the advantages of theoretical analysis of load behavior with the practical benefits of observed end-use load characteristics. Most of the overseas work on end-use modelling has centered around residential electricity use and a little on commercial end-use analysis. The wide range of electricity end-uses in industrial applications has precluded these classes from much end-use load research.

4.1.4 The Contribution to Load Factor (CLF) Method

This technique, based on a combination of the assumed load factor method and the disaggregation method, was first noted in a UNIPEDF manual as used by the CEBB [UNIPEDF 1972] and recently reported again at the AEIC annual Load Research Workshop in 1990 [AEIC 1990c]. The contribution of each disaggregated customer class to the system load factor is calculated and used to predict demands using energy sales forecast figures. It depends on the historical relationships between class sales and demands. The impacts of external influences such as weather are then used to modify the model. CLF demand forecasting can cater (to a certain degree) for structural changes in the system composition. However, the impact of market intervention or DSM programs cannot be easily included. CLF should be seen as an intermediate stage forecasting technique, between ALF forecasting and disaggregation or end-use aggregation forecasting. The information required by this technique usually exists within a utility's Load Research Department.

4.1.5 The Most Suitable Method for Eskom

The CLF technique could be implemented immediately, but the benefits of CLF over ALF were expected to be marginal due to the difficulties of including external influences. The ideal of a complete end-use aggregation model would be a costly exercise requiring several years to develop. A disaggregation model with end-use aggregation sub-models for specific critical customer classes, such as Electrification, was considered the most practical approach.

4.1.1 Econometric Peak Demand Models

Econometric demand forecasting models are based on historical relationships between system peak demand and several economic variables. These may include class sales, economic growth, population growth, and appliance saturation levels. These models tend to be based on overall economic indicators with little detailed information on customer class characteristics. The main advantage of this approach is that the historical relationships between the econometric variables and peak demands can be determined and explained. A major disadvantage is that these models assume that past relationships between econometric variables and peak demand will continue into the future. For Eskom, this assumption can no longer be regarded as acceptable, as the system demand profile is currently undergoing some serious structural changes.

3.1.2 Disaggregation Models

If the system demand profile for previous years has been disaggregated into profiles for each of the major customer classes, sales forecast figures can be applied to the class shapes. The shapes are then adjusted, if necessary, to cater for external influences, and recombined to produce an estimated demand profile shape. Estimates for the impact of DSM programs, and emerging new customer classes, such as recently electrified communities, can be included in the recombination process. The degree of disaggregation varies from utility to utility, and can range from as few as three to over one hundred customer classes. The advantages of this technique are that relatively quick (one to three years) changes in the system makeup predicted by energy sales forecasting can be included in the model, and that the models are relatively cheap and can be easily developed. Disadvantages are that the accuracy of the disaggregated category profiles is critical, and that the sales forecast customer classes may not coincide with the disaggregation classes. Although changes *between* classes are catered for, changes *within* classes are beyond the scope of this approach. DSM impacts can be included in forecasts as separate estimated classes. Since these models are often based on average weeks or days, the impacts of external influences such as weather are difficult to cope with.

4.1.3 End-Use Hourly (Aggregation) Models

This is a 'bottom-up' approach, where demand profiles and characteristics for each of the electrical end-uses are combined or aggregated to produce a system demand profile. There may be, for example, fifteen residential end-uses, ten commercial, and several industrial end-use classes. As with the disaggregation approach, demand profile modifiers for DSM measures or external influences may be included. In this case these can be applied to each end-use or class profile. These models incorporate a lot of detail and are consequently very expensive. This is probably the most accurate technique in rapidly changing utility circumstances. Due to the associated high costs, very little end-use load research has been done in South Africa, and only in the domestic and commercial areas.

Chapter 4 : The Experimental Demand Forecasting Model (XDFM) Development

4.1 ALTERNATIVES TO THE ALF METHOD

The ALF method relies on a stable relationship between energy sales and annual maximum demand. Several structural changes taking place in the electricity supply industry were actively altering this. These were discussed in Chapter 3 and include the following:

- **The changing customer mix.** The proportion of manufacturing industry, commercial, and residential load was increasing rapidly. The prospects for more large energy-intensive base load plants looked bleak. This implied that the high proportion of base load to which Eskom was accustomed would not be maintained.
- **The introduction of DSM interventions in the market by Eskom.** These included Tariff E in 1986, followed by Tariff T in 1990. These tariffs have since been renamed to Nightsave and a range of TOU tariffs Megaflex, Miniflex, and Ruraflex. These tariffs have the effect of limiting peak demand growth relative to energy sales growth.
- **The national electrification program initiated in 1990.** The impact of electrifying an additional 3 million homes by 2000, effectively more than doubling the number of residential customers in the country, was bound to have serious implications for Eskom's peak demands. Residential load is naturally peaky, resulting in disproportionate growth of the morning and evening peaks.

The above impacts were bound to affect the peak demand forecasts using ALF. The forecasting dilemma that Eskom faced was experienced by many North American and European utilities during the Seventies as a result of the oil crisis of 1973. Many of these utilities had been successfully using the assumed load factor method of maximum demand forecasting. The sudden change in the energy - demand relationship due to the introduction of conservation and DSM measures in the late Seventies highlighted the inability of this technique to accurately track these changes. This led to the development of more sophisticated energy and demand forecasting techniques by many utilities and other organizations. Most of the demand forecasting methods depend on the energy sales forecasts, merely using different methods of deriving expected maximum demands from expected energy sales figures. All of the more sophisticated methods make use of load research data to model the components that make up the system load. Four of these techniques will be discussed briefly.

a) **Objective Definition** : The primary objective was clearly defined and well understood. The secondary aim, determining the demand impact of Tariff E, was not. A clear definition of 'demand impact' was not provided. This aspect was rated at 80%.

b) **Data Adequacy** : The sample data available for the system disaggregation was poor in terms of quantity, but of good quality. The samples for each class were predetermined and generally not representative when measured by the usual techniques. Access to confidential customer billing data by Load Research staff was restricted in 1991, and this hampered the sample design and validation process. This problem no longer exists. The good results had more to do with Tariff A (for base load customers), good weather, and luck, than quality of class samples. This aspect of the project was poorest, rated at 40%, and is the area that demanded the most attention for future attempts at disaggregation.

c) **Analysis Methods** : As the first such analysis done by Load Research, it was a success. Computing facilities and software used was adequate. The team was well able to make the best use of limited data, and techniques new to the team were used successfully. This aspect was rated 75%.

d) **Reporting** : As well as the usual internal report, this project resulted in a paper published at a SAIEE conference [Bluff 1992] and presentations to several audiences in Eskom, as well as at the AEIC Load Research Workshop in the USA [Berrisford 1993a]. Apart from the actual value of the result, to Eskom management, considerable publicity and support for Load Research was achieved by the project. This aspect rates 80%.

3.10. CONCLUSION

Although the average winter weekday model was very close to the actual system demand profile, there were several aspects of the project that warranted a lot of attention. The most serious of these was sample design and selection. An innovative technique of sample validation was successfully used to overcome the limitations of more usual methods, when samples are small and predetermined. This technique needs to be tested more rigorously before being considered for general use, and is probably unsuitable for applications such as rate case hearings, as presently done in the USA. The system model results were more accurate than the underlying sample confidence and reliability might indicate. Overall the project was regarded as successful.

research nature. An attempt was made to evaluate the project loosely along the lines suggested in the AEIC Load Research Manual (1990 Edition) [AEIC 1990a].

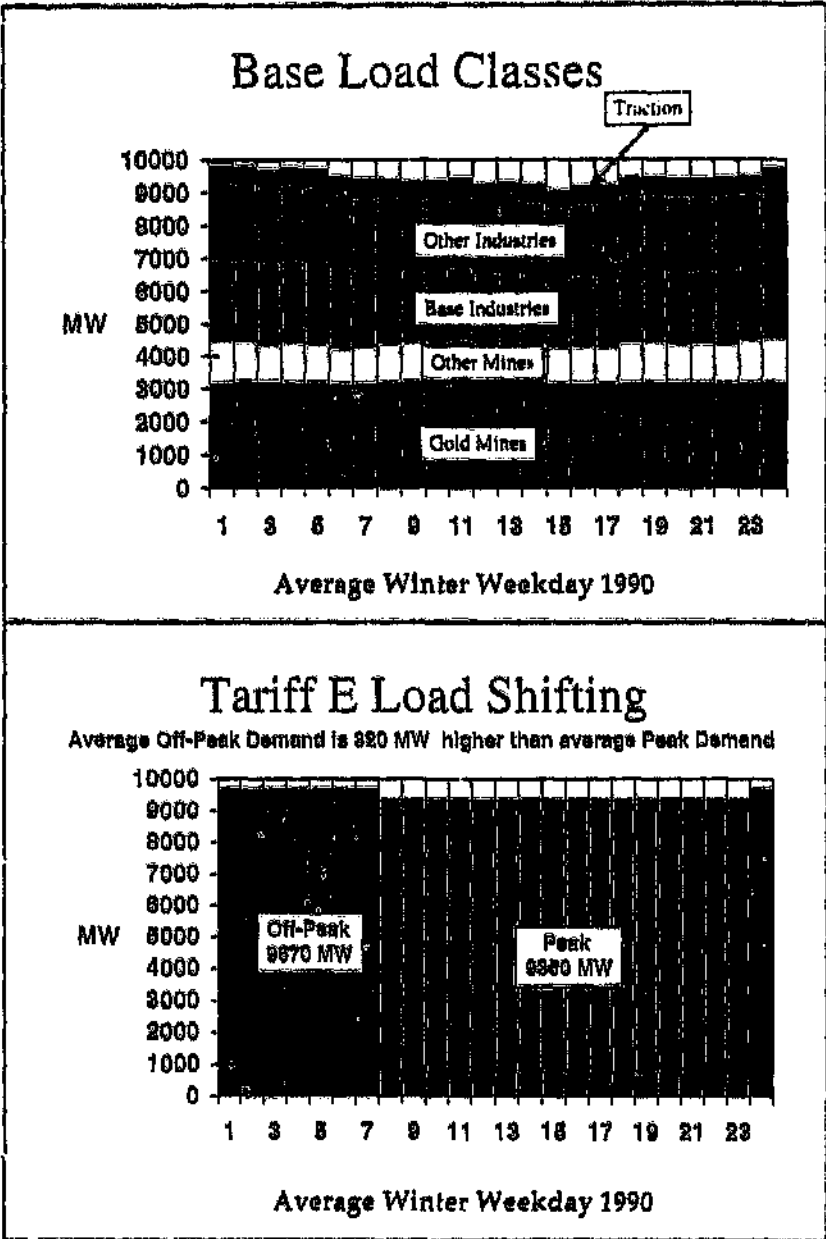


Figure 3.12 Tariff E Load Shifting

customers in 1990, only 45 incurred off-peak maximum demands. Of these, several appeared to have off-peak MDs by chance rather than design, and only 3 or 4 times per year. It seems that two thirds of the Tariff E customers could not or would not make use of the tariff. In fact several municipalities that would never incur off-peak MDs are billed on Tariff E. It was also noted that one Tariff E customer in the

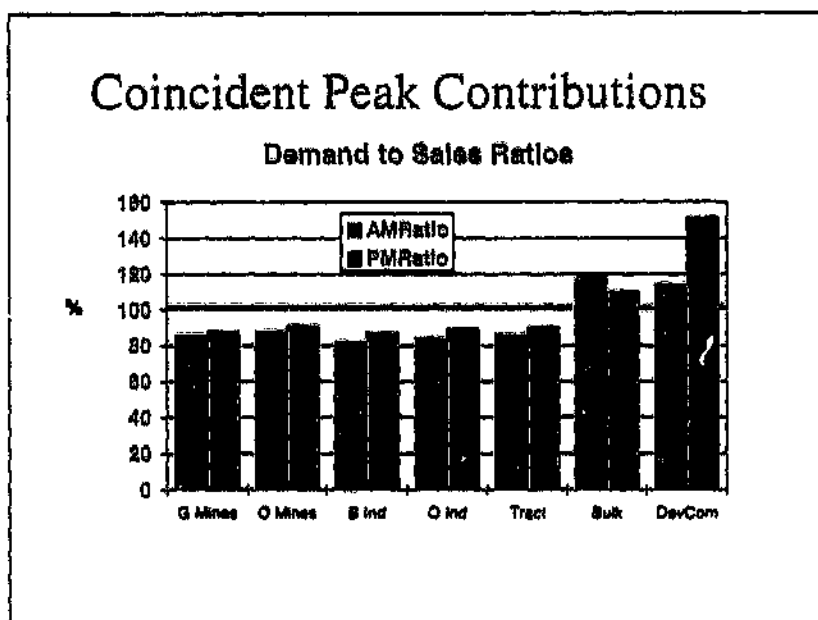


Figure 3.11 - Proportional Peak Contributions of Customer Classes

sample made use of the weekends to increase demand, but did not consider this worth while during the 8 hour off-peak periods between Mondays and Saturdays.

As can be seen from the disaggregated system demand profile, the base load (Figure 3.12) dropped slightly after 06h00 and picked up again at 23h00. The average on-peak demand for the base load class was 320 MW lower than the average off-peak demand. This is an indication, within the accuracy constraints of the model, of the load shifting which had occurred due to Tariff E. It was assumed that all customers that shifted load on Tariff E would have had average daily load factors above 95% had they been on Tariff A. Assuming that energy sales to Tariff E customers would have been the same under Tariff A, this implies an average decrease of 107 MW during the 16 peak hours and an increase of 213 MW during the 8 off-peak hours. The impact of Tariff E can thus be estimated as 107 MW, 213 MW, or 320 MW, depending on one's definition.

3.9. PROJECT EVALUATION

During 1989 and 1990 the efforts of the Load Research team were centered around gathering customer demand profiles for evaluation of the proposed TOU tariff for large customers. This system disaggregation was the first project of a truly load

| Customer Class | Annual Sales Contribution | Morning Peak (09H00) | Evening Peak (19H00) |
|------------------------|---------------------------|----------------------|----------------------|
| Developing Communities | 2,9% | 3,3% | 4,4% |
| Bulk & Other | 44,2% | 52,0% | 49,1% |
| Traction | 2,9% | 2,5% | 2,6% |
| Other Industries | 12,3% | 10,3% | 11,0% |
| Base Industries | 12,8% | 10,5% | 11,1% |
| Other Mines | 6,9% | 6,1% | 6,3% |
| Gold Mines | 17,6% | 15,2% | 15,5% |

Table 3.8 : Coincident Peak Contributions

The smallest class ('Developing Communities') had the largest proportional impact on the morning and evening system peaks. This was also the class with the most potential for significant growth, as a direct result of the national electrification program [Berrisford & Bluff 1991]. This class and the 'Bulk' class together contribute 47.1 % to the total consumption, but 55.3% and 53.5 % to the morning and evening peaks respectively. The other classes actually contribute less to the peaks than to the average consumption, depicting their base load nature.

3.8.3 Annual and Summer Models

A system disaggregation for the Average Summer Weekday and the Average Annual Weekday for 1990 were done as well. These models were not as accurate as the winter model, due to the longer periods and greater weather and economic variations in the system demand patterns. They were nevertheless considered acceptable. The key statistical indicators for the summer and annual models are tabled below.

| | MAPE | Rank Correlation |
|------------------------|-------|------------------|
| Average Winter Weekday | 1.00% | 0.98 |
| Average Summer Weekday | 1.29% | 0.92 |
| Average Annual Weekday | 1.25% | 0.97 |

Table 3.9 - Key Statistical Indicators

3.8.4 The Demand Impact of Tariff E

A small number of customers are billed on Tariff E, a two-part tariff in which customers are billed for maximum demand occurring only during on-peak times (07h00 to 23h00 weekdays). Since its introduction in 1986 Eskom had not been able to monitor the impact of this off-peak tariff on the system demand profile. The author was requested to do this if possible. Since Tariff E is identical to Tariff A, except that off-peak MD is not measured for billing purposes, a customer cannot lose by opting for Tariff E. If his MD occurs during off-peak times, he will gain. If not, he will pay the same as he would on Tariff A. This resulted in a number of customers converting to Tariff E but not actively responding to the off-peak message. Of the 156 Tariff E

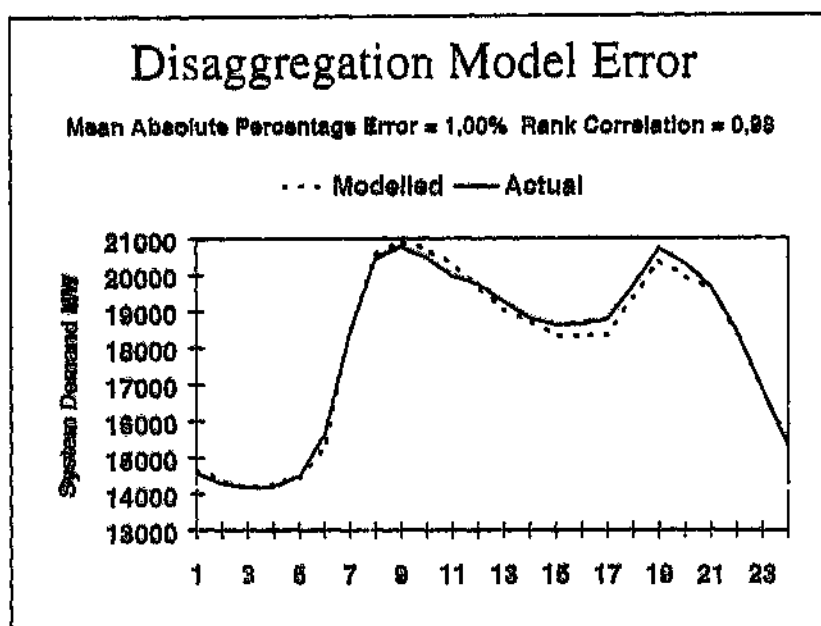


Figure 3.10 - Comparison of Actual and Modelled System Demand Profile

The correlation between the model and the actual average winter weekday was a lot better than had been expected, considering the poor samples, particularly in the 'Industrial' class.

These good results were attributed to the following factors:

- The high demand charge of Tariff A, which resulted in good demand management by the 'Mining' and 'Industrial' classes.
- Regular weather patterns during the winter of 1990.
- The consistent generic shapes of both 'Bulk' and 'Developing Community' class.

3.7.2 Coincident Peak Contributions

The base load is made up of the 'Mining', 'Industrial' and 'Traction' classes, all of which clearly exhibit excellent load factors. The response to Tariff E is evident in the Industrial classes, as a reduction in demand after 07h00 followed by a corresponding increase at 17h00. The urban commuter peaks in the morning and evening are visible in the Traction profile. These traction peaks are earlier than the system peaks. The 'Bulk' and 'Developing Communities' class make the major contributions to the morning and evening system peaks. The demand contributions of each class are listed in Table 3.8, with proportional contributions to morning and evening peaks illustrated in Figure 3.11.

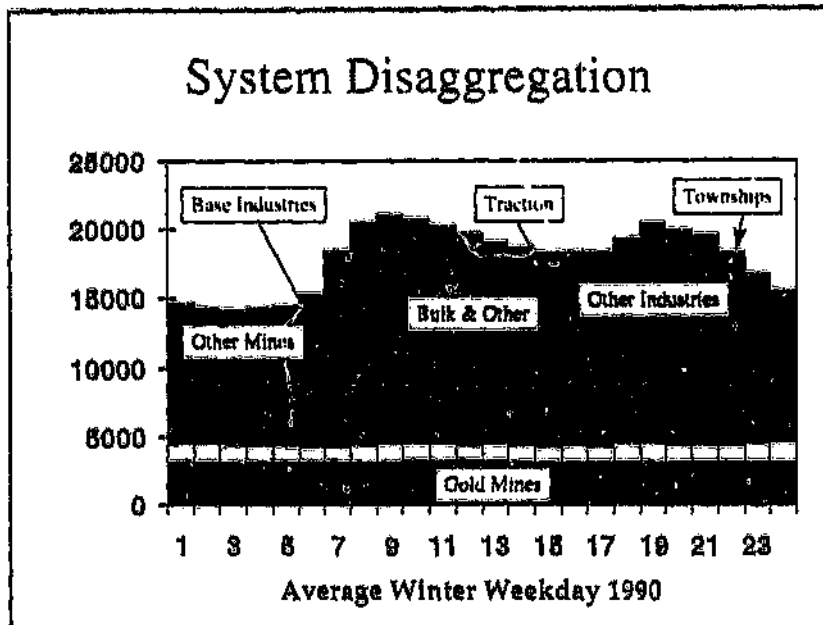


Figure 3.9 - System Disaggregation of the Average Winter Weekday 1990

The system model built up from these seven class is shown in Figure 3.9. From bottom to top the classes are Gold Mining, Other Mining, Base Industries, Other industries, Traction, Bulk & Other, and developing Communities.

3.7.1 Validation of the Model

The actual average winter weekday system demand profile was compared to the modelled profile. Both are shown in Figure 3.10.

The mean absolute percentage error (MAPE) and Spearman rank correlations were calculated. The MAPE was 1.0% and the rank correlation was 0.98. The model slightly overestimated the morning peak and underestimated the evening peak by about 1%. It is suspected that the Bulk & Other sample did not capture the peakiness of many smaller municipal customers adequately. Nevertheless, this model was as good or better than similar models by other utilities, such as that of the CEOB in 1986 [Allera & McGowan 1986]

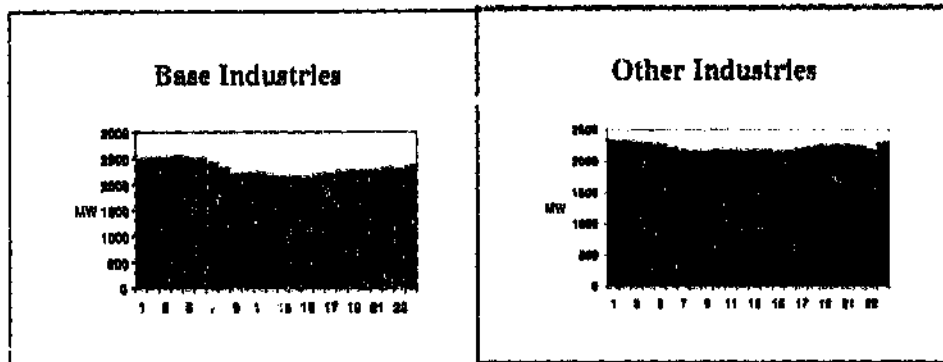


Figure 3.6 - 1990 Average Winter Weekday Profiles of Base Customer Classes

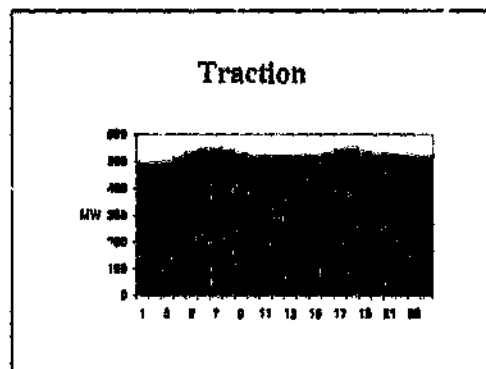


Figure 3.7 1990 Average Winter Weekday Demand Profile of Traction

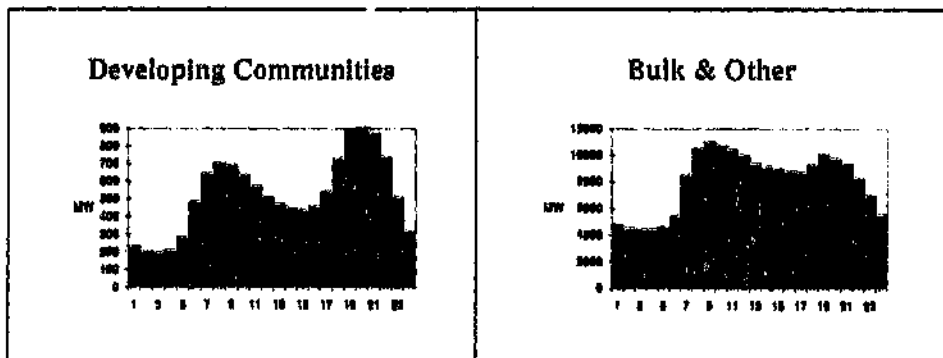


Figure 3.8 - 1990 Average Winter Weekday Profiles of Peak Customer Classes

The total system demand for each hour of the average winter weekday was then determined by summing the hourly demands for all the classes.

$$S(t) = \sum_{j=1}^m K_j(t) \quad (3.6)$$

where:

- $S_{ij}(t)$ is the average winter weekday demand of customer i of the sample for class j at hour t
- d is the number of winter weekdays
- $D_{nij}(t)$ is the demand of customer i of class j on winter weekday n at hour t
- $K_j(t)$ is the AWW demand of class j at hour t
- k is the number of customers in the sample for class j
- P_j is the winter consumption of the population of class j
- Q_j is the winter consumption of the sample of class j
- $S(t)$ is the AWW system demand at hour t
- m is the number of classes making up the system.

Average winter weekday profiles for each of the seven class are shown below (Figures 3.6 to 3.8).

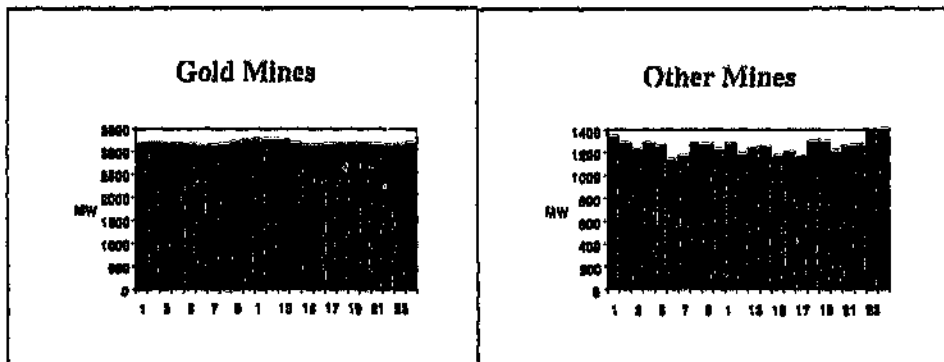


Figure 3.6 - 1990 Average Winter Weekday Profiles of Base Customer Classes

The model then summed the five classes to provide a system 'Total Sales' AWWk profile. This was then increased by 5.3% to include system losses to provide a 'Nett Sent Out' AWWk profile. (This has the same effect as adding proportional losses to each class, but involves less arithmetic.)

The Forecast System Demand Profile table consisted of the Total Sales and Nett Sent Out columns for 1990, 1991, and 1992.

The actual AWWk profiles for 1991 and 1992 were then derived and included to allow testing of the model output.

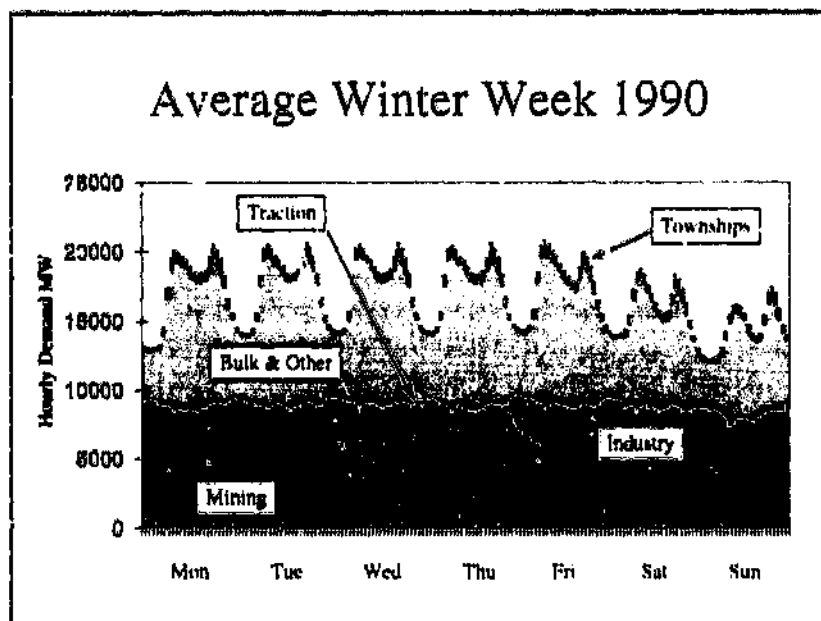


Figure 4.12 - The Prototype Average Winter Week for 1990

The stacked average winter week profile is shown in Figure 4.12. The week starts on Monday, and the reduced weekend demand is clearly visible, as is the typical weekday shape, with Mondays and Fridays being slightly different to midweek days.

catered for three years (1990, 1991, 1992). The spreadsheet consisted of input data tables, aggregation model calculation tables, and output tables (Figure 4.11). The Seasonal Correction Factors were included in the aggregation model tables, to allow the flexibility of using different factors for each year.

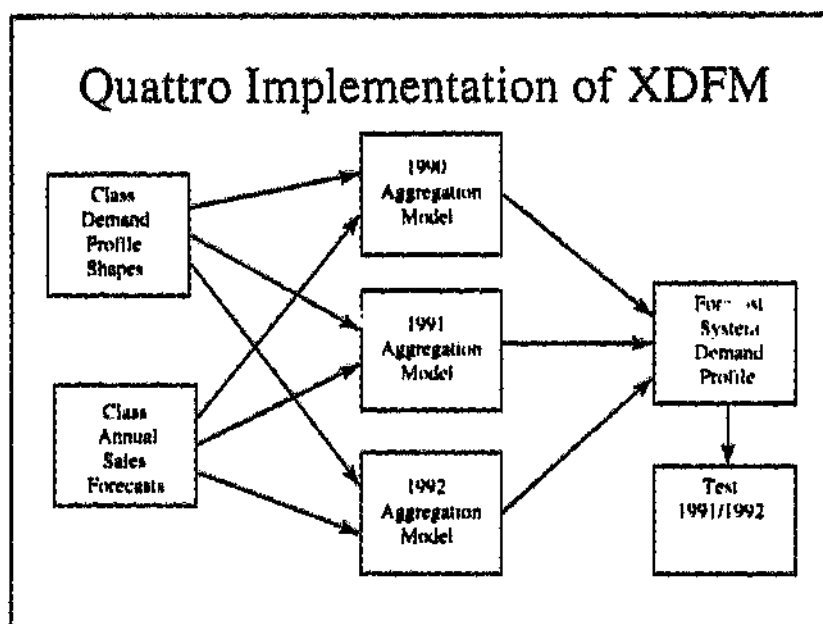


Figure 4.11 - The Quattro Implementation of XDFM

The Class Demand Profile Shapes were the shapes of the Average Winter Week profiles of the class samples (in 1990), normalised to a weekly energy content of unity. (This made it easy to generate class AWWk profiles from annual class sales and the SCF.)

The Class Annual Sales Forecasts consisted of a table of class sales as reported in the Statistical Yearbook [Eskom 1990] and summated to produce annual sales figures for the five classes for which demand profiles were available.

The model tables calculated the AWWk hourly demand of each class as follows:

$$D_j(t) = S_j(t) \cdot G_j / 52 \cdot H_j \quad (3.4)$$

with:

- $D_j(t)$ is the forecast demand of class j at hour t
- $S_j(t)$ is the normalised demand of class j at hour t , from the class profile shape
- G_j is the annual sales of class j for the forecast year
- H_j is the Seasonal Correction Factor for class j

the Management Information Decision Support (MIDS) system in Eskom. MIDS is a mainframe database which lists key billing data for each (large) customer.

Since long term energy forecasts are based on annual sales and not monthly sales, a seasonal correction factor had to be estimated for each class. The actual ratios of winter sales to annual sales for 1990 (Figure 4.1) were initially used. It was later noted that these ratios varied slightly from year to year (Figure 4.10), and averages of the ratios for the period 1989 to 1992 were used.

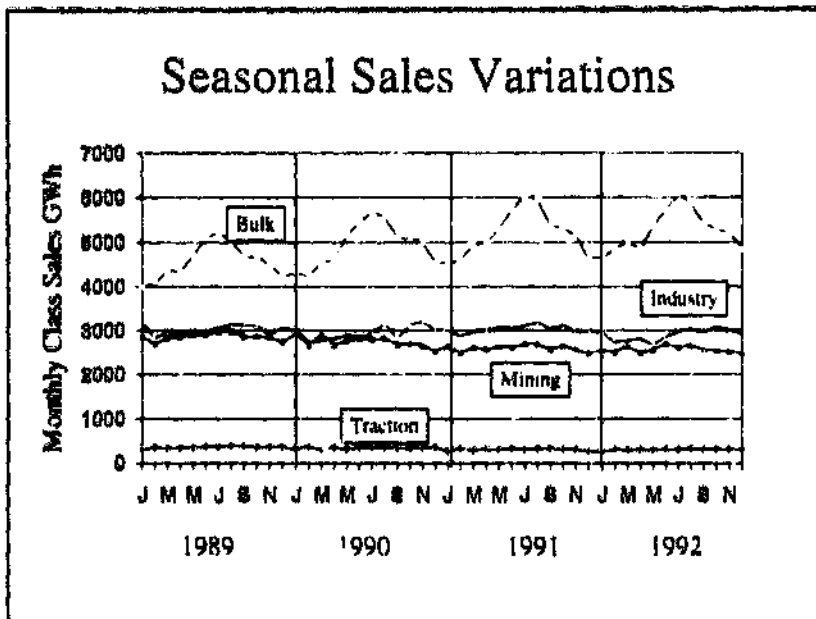


Figure 4.10 - Seasonal Sales Variations

4.4.3 The System Demand Profile

The actual hourly Net Sent Out (NSO) figures for the integrated Eskom system were obtained from the National Control Center at Simmerpan, where the System Operations Department recorded the output of each power station from a country-wide SCADA system. These data were required to test the aggregation model. The NSO figures represented the sum of all customer sales plus transmission and distribution losses, estimated at about 5.3% of total sales for 1990.

4.5 IMPLEMENTING THE MODEL

4.5.1 The first (prototype) demand profile forecasting model

The XDFM was initially implemented as a Quattro spreadsheet, which was later moved to Excel and implemented as a workbook. The initial Quattro spreadsheet

each customer class, and a modification to the aggregation model to implement the target year ratio expansion and SCF.

Any changes in the system demand profile shape that are due to different class growth rates will be captured by the model. However, any changes due to external influences unknown to the model would be evident as a difference between the forecast profile and the actual profile.

4.4 DATA FOR THE XDFM MODEL

There were three data sets required for the prototype XDFM model. These were the class demand profiles for the winter of 1990, the class energy sales figures for 1990 to 1992, and the system Net Sent Out (NSO) demand profiles for 1990 to 1992.

4.4.1 Class Demand Profile Shapes

The class demand profiles were derived from the 1990 disaggregation project. Although the samples were predetermined, the accuracy of the final disaggregation model indicated a high degree of confidence in the class demand profiles. The hourly or half-hourly demand profiles for all 132 sample customers for the three winter months were used as raw data. These demand profiles were processed to derive Average Winter Week profiles for each customer (Equation 4.1). It was then discovered that a few customers in two of the samples had experienced abnormal loads for portions of the winter period, which were evident in the AWWk profiles (although not apparent in their AWW profiles). These customers were in the Other Mining and Other Industries classes. These 'bad' customers were removed from the samples. This degraded the representative quality of the samples for these two classes. After some experimentation, it was decided to combine the remaining Other Mining sample customers with Gold Mining, and Other Industries with Base Industries. This resulted in only five customer classes, namely:

- All Mines (Gold Mining with Other Mining)
- All Industries (Base Industries with Other Industries)
- Traction
- Bulk & Other
- Townships

Although this is far from ideal it was felt that five classes would be sufficient to illustrate the principles of the model, and hopefully, to isolate the impacts of the external influences.

4.4.2 Class Energy Sales Figures

Annual energy sales figures were obtained from the Eskom Statistical Yearbook for 1993 and monthly sales figures for sample customers and classes were extracted from

The demand profile forecasting model is similar to that of the previous disaggregation model, consisting of averaging and summation processes. The first step is to determine the average winter week (AWWk) demand profile for each customer in each class sample. In this case the averaging takes place over 13 weeks rather than 65 weekdays, as with the disaggregation project.

$$S_{ij}(t) = \frac{1}{d} \sum_{n=1}^d D_{ni}(t) \quad (4.1)$$

The second step involved creating the AWWk profile for each sample by summing the individual customer profiles in each sample. The average winter week profile for each class was then produced by expanding the sample average winter week profiles using simple ratio expansion. The ratio for forecasting is the target year annual class sales to the base year sample sales. This differs from the aggregation model which uses base year sales for both sample and class. For an Average Winter Week model using annual class sales figures, a Seasonal Correction Factor (SCF) is required for each class. This is to allocate the correct proportion of annual sales to the winter season for each class. At this time the 5.3 % distribution system losses were proportionally allocated to each class.

$$K_j(t) = \sum_{i=1}^k S_{ij}(t) \cdot \frac{G_j}{Q_j} \cdot H_j \cdot 1.053 \quad (4.2)$$

The total system demand for each hour of the average winter week was determined by summing the hourly demands for all the classes.

$$F(t) = \sum_{j=1}^m K_j(t) \quad (4.3)$$

where:

- $D_{ni}(t)$ is the demand of customer i of the sample for class j for winter week n at hour t
- d is the number of winter weeks (13)
- $S_{ij}(t)$ is the AWWk demand of customer i of class j at hour t
- $K_j(t)$ is the AWWk demand of class j at hour t
- k is the number of customers in the sample for class j
- G_j is the target year annual consumption of the **population** of class j
- Q_j is the base year annual consumption of the **sample** of class j
- $F(t)$ is the Average Winter Week system demand at hour t
- m is the number of classes making up the system.
- H_j is the Seasonal Correction Factor (SCF) for class j

Figure 4.9 shows the components of this forecasting model. The only additions to the disaggregation model are target year annual (or seasonal) energy sales forecasts for

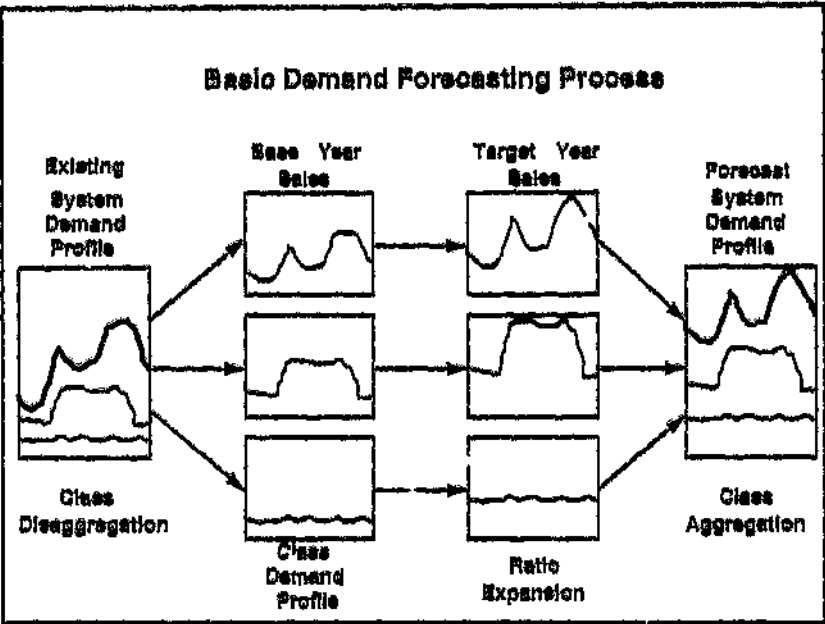


Figure 4.8 The Basic Demand Profile Forecasting Process

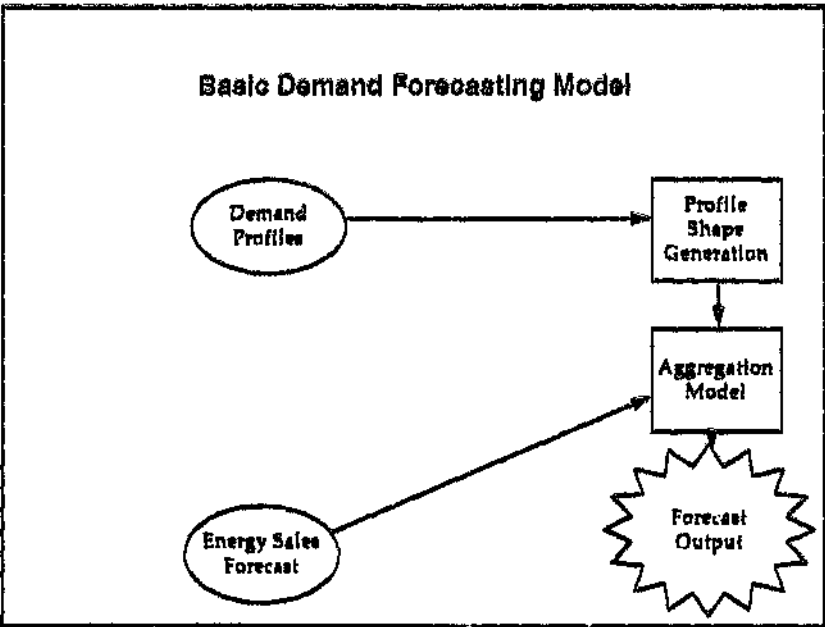


Figure 4.9 Basic Demand Profile Forecasting Model

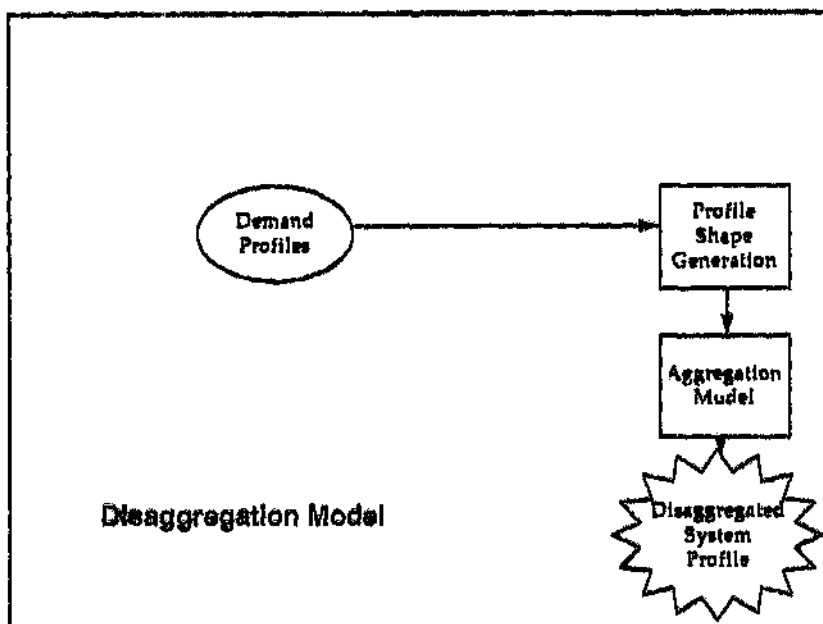


Figure 4.7 Components of a Disaggregation Model

4.3.2 Demand Profile Forecasting Structure

The disaggregation project provided the author with fairly accurate estimated class demand profiles for the winter of 1990. Using the annual sales figures to each class for 1991 and 1992, it was possible to 'forecast' the system demand profile from 1990 class demand profiles by using the ratio expansion process again, as shown in Figure 4.8. The hourly demand for each class is increased (or decreased) by the ratio of the target year sales to the base year sales for the class.

The experimental demand profile forecasting model was based on this representation, and initially only the winter season was considered. The XDFM was therefore designed to forecast the average winter week (AWWk) using annual sales forecasts for each class.

4.3 THE AGGREGATION MODEL PROCESS AND STRUCTURE

4.3.1 The Aggregation Model Process

The aggregation process is illustrated in Figure 4.6. The total system demand profile consists of the sum of the profiles of each customer class. In order to estimate the profile shape of each class, demand profiles of a sample of customers that represent the class are collected. These data are then aggregated and expanded ratiometrically to produce the estimates of the class demand profiles. The class demand profiles are then aggregated to produce an estimate of the system demand profile.

Figure 4.7 shows the components that make up such a model. The primary components are the raw demand profile data sets for the sample customers, the class demand profile shape generation model, and the aggregation model itself.

The accuracy of the model can be determined by comparing the actual system demand profile to the modeled profile. This process is described in Chapter 5.

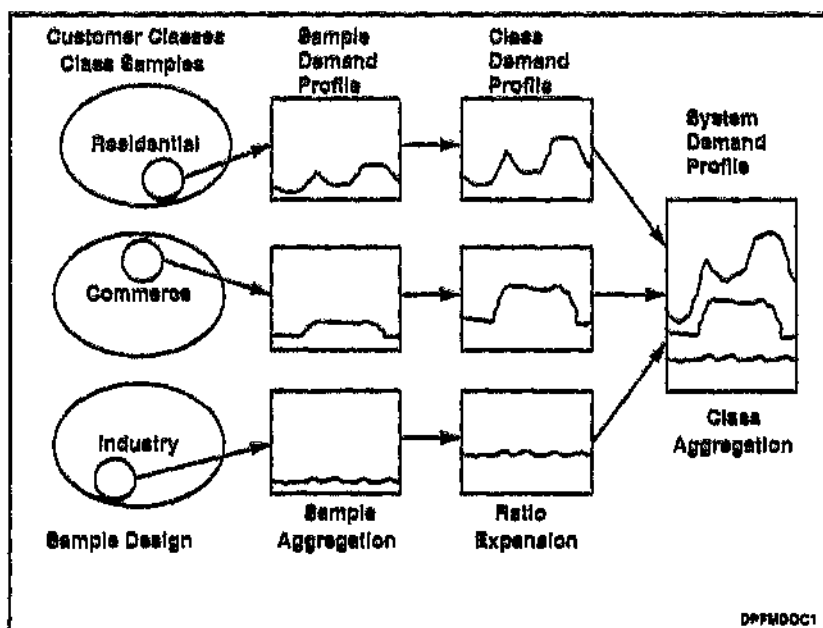


Figure 4.6 - The Aggregation Model

- A **Winter** season consisting of weeks 23 to 35. This 13 week period is coincidentally within a few days of the calendar months June to August.
- A **Postwinter** period with the remaining weeks bar the last two of the year
- **Holiday Weeks.** The first week, the Easter week, and the last two weeks of every year do not fall into one of the above categories. Although the first and last weeks of the year are fixed, the Easter week moves from year to year.

The K-Means clustering for 1991 with four clusters is illustrated in Figure 4.5. As can be seen, there are a few Prewinter weeks in the Postwinter period and vice versa. This was a common occurrence in the analysis. The four Holiday weeks are also clearly discernible.

4.2.4 The Representation for XDFM

Based on this analysis it was decided to ignore the four holiday weeks and represent the system demand profile with three seasons. These were defined as follows:

- **Prewinter,** weeks 1 to 22, 22 weeks long.
- **Winter,** weeks 23 to 35, 13 weeks long.
- **Postwinter,** weeks 36 to 52, 17 weeks long.

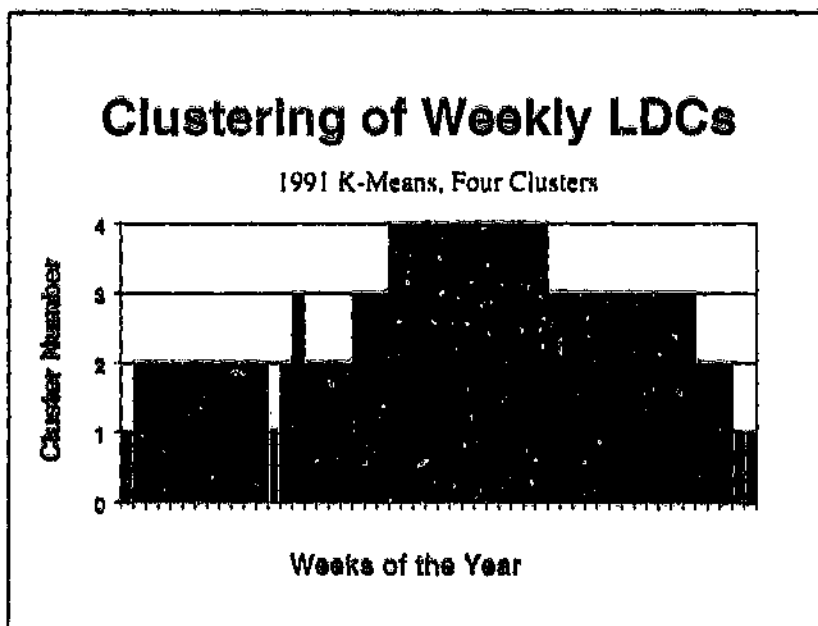


Figure 4.5 Clustering of Weekly LDCs

4.2.3 Analysis of the System Demand Seasonal Components

The author carried out a cluster analysis on the weekly LDCs for 1990, 1991, and 1992. This was done in STATISTICA, and the following options were explored:

- Three clustering techniques were used. These were Euclidean Tree, Two Way Branching, and K Means Clustering.
- Each technique was tried with the number of clusters varying from two to six.
- Each combination was evaluated for actual weekly LDCs (to include both shape and magnitude variations) and normalized weekly LDCs (to cluster only shape variations).

The outcome of this exercise was a set of observations that provided a defensible basis for defining a load shape representation. The K Means method of clustering gave the most consistent results, which were as follows:

- Normalizing the weekly LDCs to remove the effect of magnitude from the evaluation resulted in inconsistent results.

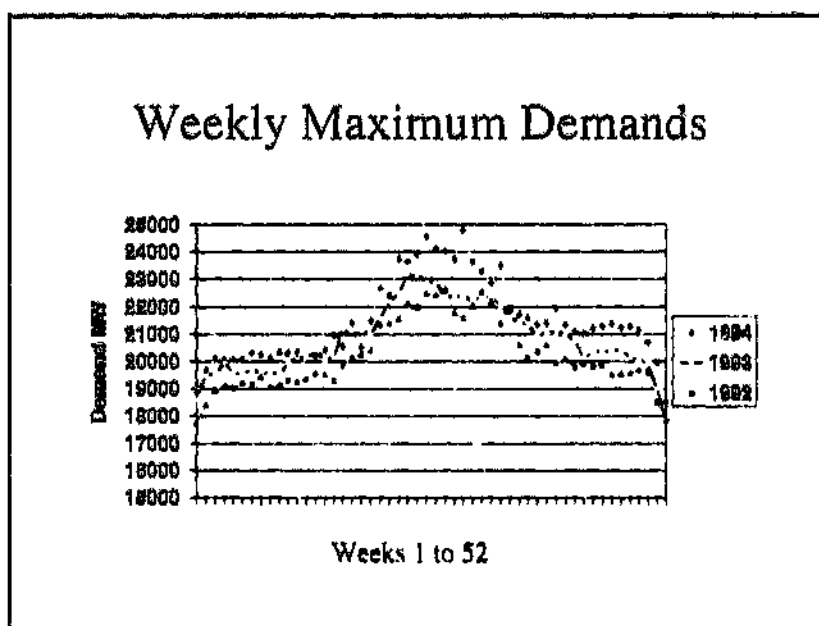


Figure 4.4 - Eskom Weekly Peaks for 1992 to 1994

- The optimum number of clusters was four. This resulted in consistent and distinct sets of weekly LDCs with the following characteristics:
 - A Prewinter season comprising weeks 2 to 22, with the exception of the week including Easter Friday.

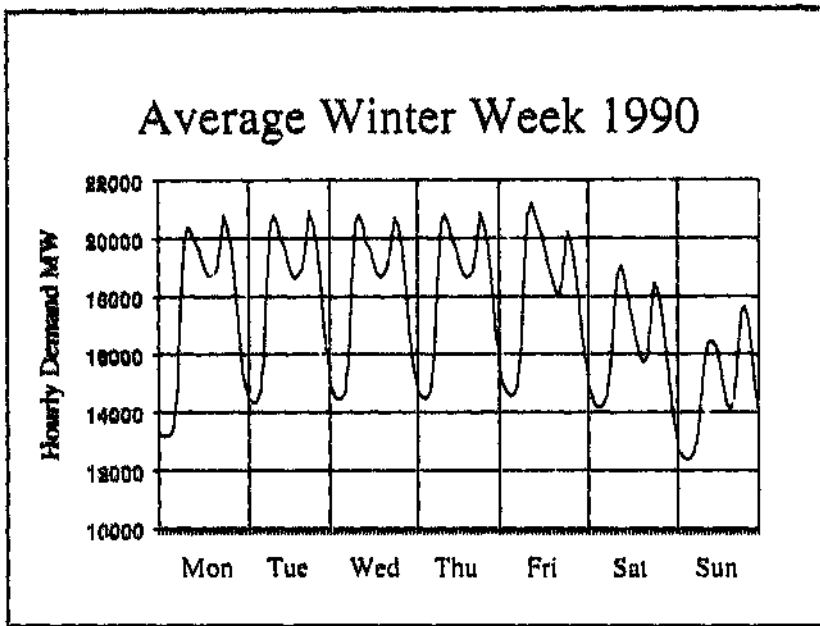


Figure 4.2 - Average Winter Week Demand Profile for 1990

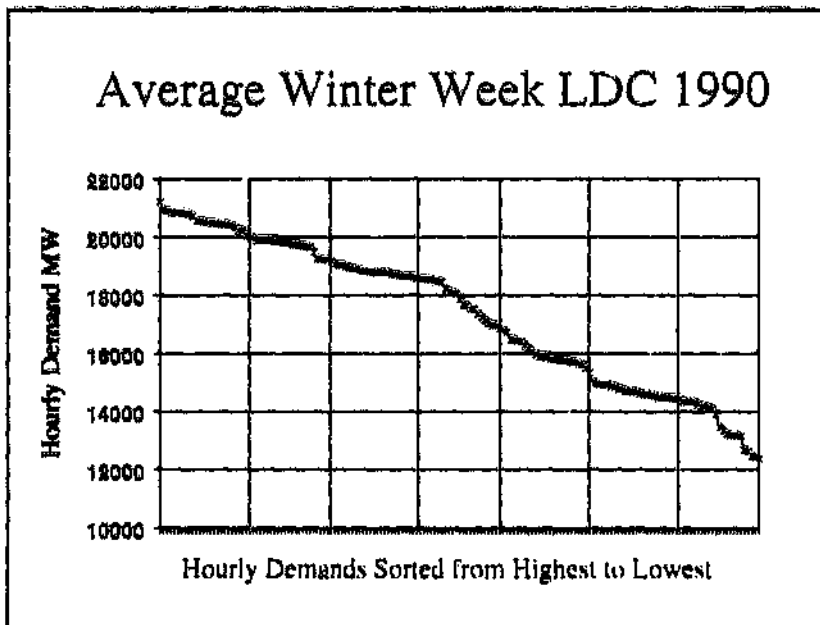


Figure 4.3 - Average Winter Week Load Duration Curve for 1990

The author felt that a multi-seasonal approach would be essential to capture the seasonal variation evident in the system profile - see Figure 4.4. However, a more scientific method of defining the number of seasons and their duration was required.

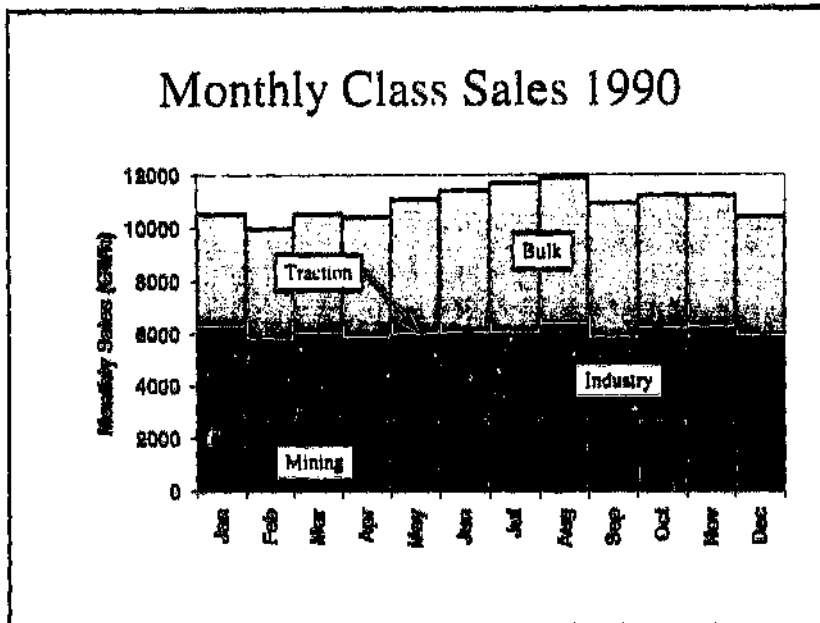


Figure 4.1 - Monthly Class Sales in 1990

- The system peak invariably occurred during a weekday. Weekend demand is lower than weekday demand. The average winter week demand profile for 1990 is illustrated in Figure 4.2
- Averaging the approximately 65 weekdays during winter increased the reliability of the model, as the averaging process filters out the effects of random external influences, such as weather variations, public holidays or serious outages. Statistically this results in 65 observations of the AWW hourly demand for each sample customer.

4.2.2 The Requirements of the Users of the Model

Discussions with the Generation Expansion Planning staff (GEP) indicated that a forecast of the average winter weekday would be of little value to them. Their planning tools used forecast weekly Load Duration Curves (LDC, see Figure 4.3) to represent system demand. GEP represented the system demand profile with an average annual LDC or at times as three average seasonal LDCs, dividing the year into three seasons with approximately equal lengths of 17 or 18 weeks each.

was derived from the feeders supplying two urban informal communities electrified by Eskom in 1990. These were Ivory Park and Orange Farm, both in Gauteng.

- **Eskom: Own Usage.** This small class, representing the load supplied to operate the transmission and distribution network, was previously included in the losses. Since this load is continuous (100% Load Factor), its consumption was extracted from the losses and included as a separate class.

6.1.2 Improving the SCF Factors

The SCF factors used in the prototype were based on the monthly billed sales to each class in 1990 (see Chapter 3). The SCF was calculated as:

$$H_j = \frac{\sum_{m=1}^{12} B_{jm}}{\sum_{m=1}^{12} B_{jm}} \quad (6.1)$$

where:

- H_j is the Seasonal Correction Factor for class j
- B_{jm} is the billed energy sales to class j for month m
- m is the billing month 1 to 12 corresponding to January to December

Billing months do not correspond to calendar months, as monthly meter readings are staggered through the last week of each month, and in some cases occur in the middle of each month. The February bill for a customer may, for example, represent the customer's consumption from the 29th of January to the 23th of February. A second customer's bill may be for the period 15th of January to 14th of February. Seasonal Correction Factors derived from billing figures were therefore suspect, and another method of deriving them was desirable to check or improve them.

| Year | Traction | Bulk | Mining | Industry |
|------|----------|----------|----------|----------|
| 1989 | 1.054448 | 1.118033 | 1.030646 | 1.013992 |
| 1990 | 1.024317 | 1.127475 | 1.021375 | 1.012962 |
| 1991 | 1.053016 | 1.133077 | 1.025481 | 1.027548 |
| 1992 | 1.039259 | 1.118337 | 1.034332 | 1.019893 |

Table 6.1 - Seasonal Correction Factors

The factors also vary slightly from year to year. The SCF figures for 1989 to 1992 are tabulated above. An initial improvement was made by averaging the calculated SCF figures for 1990, 1991, and 1992.

A second set of factors was derived by considering the model as a set of simultaneous equations. The AWWk model is actually a set of 168 models, one for each hour of the week. Each model can be represented as the sum of the demands for each class at that

Chapter 6 - Forecasting with the XDFM

The experimental model had to be expanded and modified before it could be used in practise. This chapter outlines the changes made and describes the application of the XDFM in Eskom's long term forecasting process for the 1996 Integrated Electricity Plan (IEP5).

6.1 EXPANDING THE MODEL FOR FORECASTING

The prototype XDFM was expanded in an Excel workbook to include all years from 1990 to 2015. This entailed a complete redesign of the model, and several improvements were added, including better SCF factors and tariff impact sub-models for Tariffs E and T.

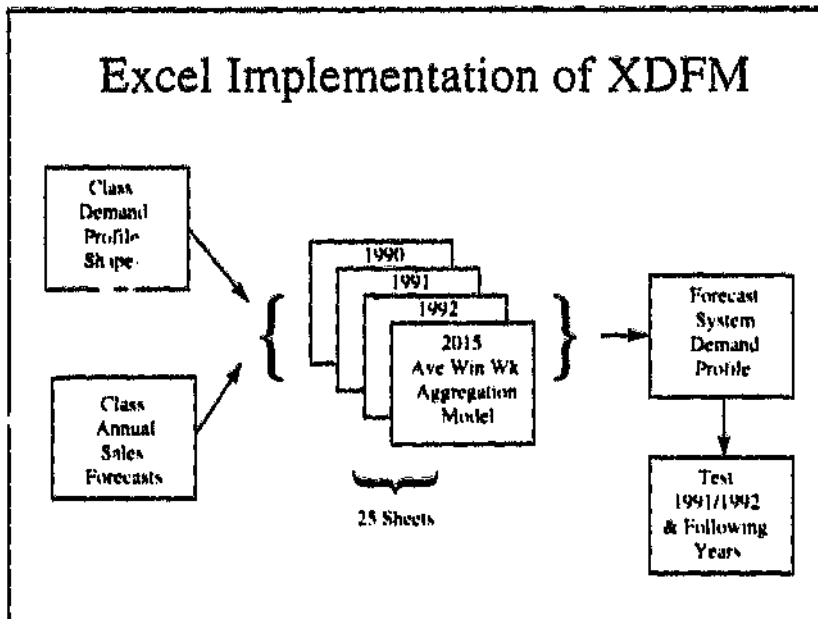


Figure 6.1 - Excel Implementation of XDFM

6.1.1 Additional Load Classes

For long term forecasting purposes a number of additional customer classes were added to the model. These included:

- **Electrification.** The national electrification program, initiated in 1990, was expected to consume a significant portion of Eskom sales by the turn of the century, even though the impact was small during the early years. The profile shape

model to isolate the type of system demand profile change currently being experienced by Eskom.

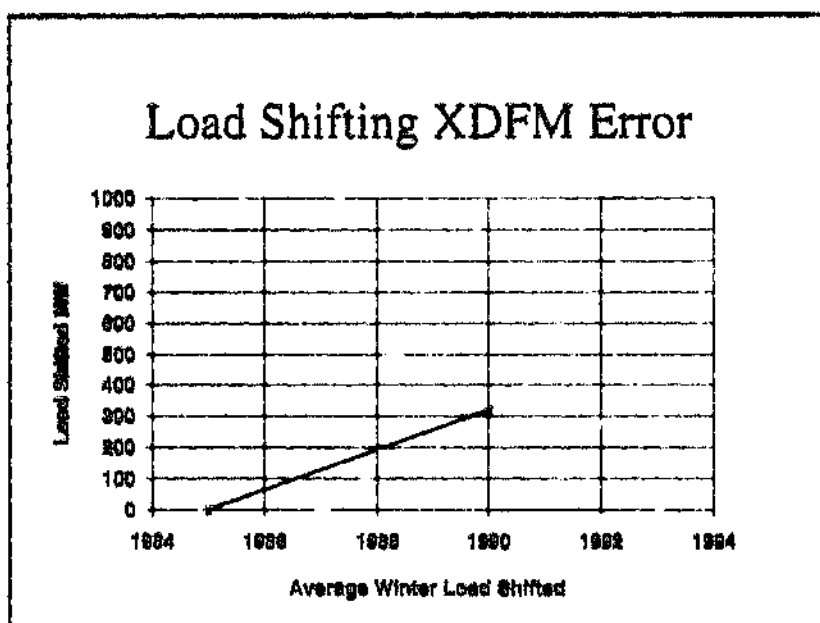


Figure 5.10 - Total Load Shifting

5.3.3 Measuring the Load Shifting in 1992

Figure 5.8 shows the error demand profile for 1992. Although the daily pattern is not as consistent as for 1991, a similar load shifting error is apparent. The procedure to extract the additional load shifting was applied, resulting in the corrected error profile shown in Figure 5.9. The correlation coefficient between the original error profile and the load shift profile was -0.7520, and after the extraction process it was 0.1158. The estimate for additional load shifting (since 1990) was about 340 MW.

This is lower than the estimate for 1991, which appeared unusual. Inspection of the 1992 annual sales for the load shifting customer classes (Mining, Industry, and Traction) [Eskom 1993] revealed a corresponding sales reduction. The reduction in load shifting was not incorrect.

5.3.4 The Electrification Impact in 1992

The total number of homes electrified by Eskom was about 300 000 by the winter of 1992. This implied an additional demand of about 180 MW during the evening peak. Sales to electrification customers in 1992 totaled about 84 GWh. This translates to an expected evening peak contribution of about 30 MW. As in 1991, this peak demand contribution was too small to be isolated by the XDFM model.

5.4 - CONCLUSION

The main descriptive statistics of the error profile before and after the load shifting are listed in Table 5.1. Both the Kurtosis and Skewness tests indicate that the error profile has a much more Normal distribution after the load shifting has been extracted.

| | 1991 | 1991 (Ld Shft) | 1992 | 1992 (Ld Shft) |
|---------------------------|---------|----------------|---------|----------------|
| Standard Deviation | 212 MW | 95 MW | 225 MW | 150 MW |
| Kurtosis | -1.4 | -0.188 | -0.57 | 0.6152 |
| Skewness | 0.0517 | 0.1472 | 0.5498 | 0.2651 |
| Correlation Coef. | -0.8897 | 0.0265 | -0.7520 | 0.1158 |

Table 5.1 - Descriptive Statistics of Error Profiles

The correlation coefficients between the error profiles before and after load shifting extraction are also included. These confirm the existence of the additional load shifting and the high degree of success in removing it from the error profile. The model could clearly isolate the additional load shifting that had occurred.

The impact of the electrification program was, however, too small to be clearly discerned.

Changes in the system demand profile structure due to the impact of Tariff E load shifting were clearly identified in this manner. These tests indicated the ability of the

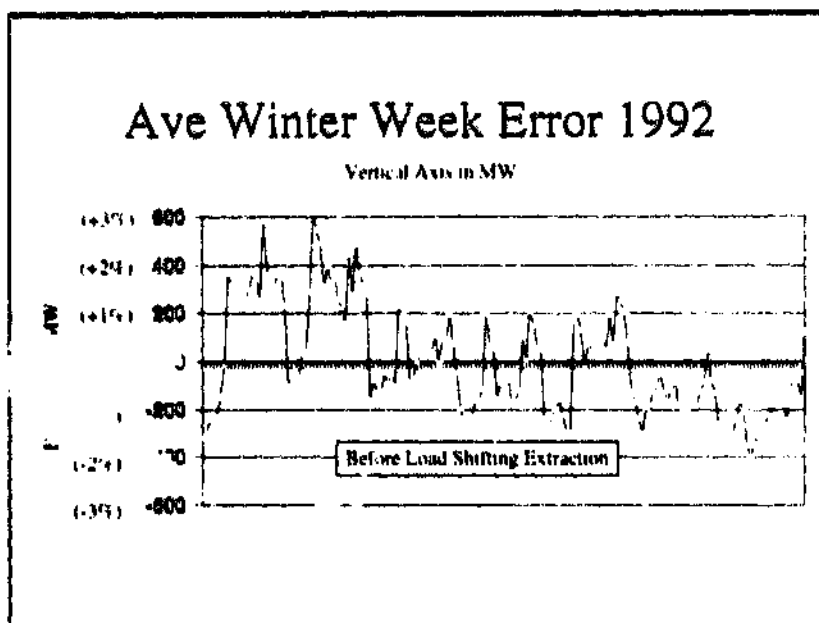


Figure 5.8 The Uncorrected Error Profile for 1992

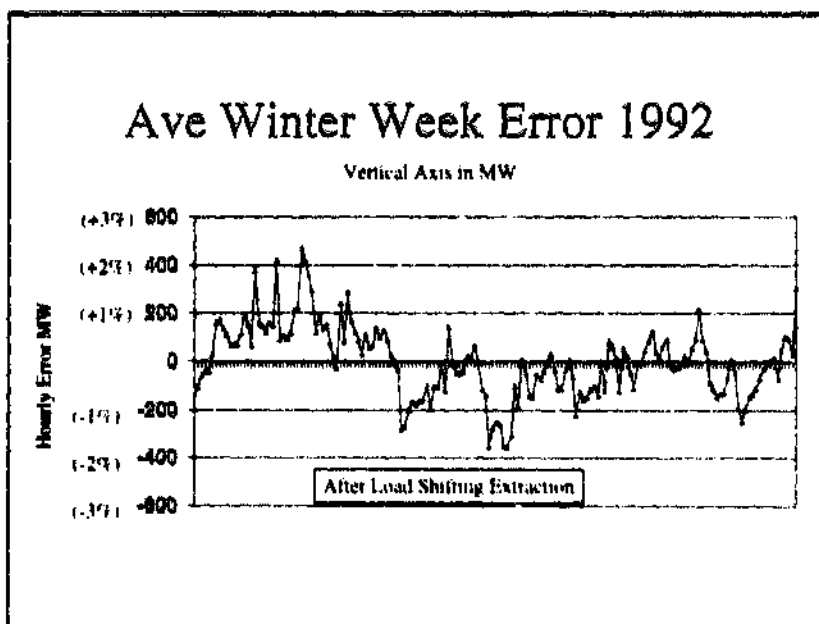


Figure 5.9 The Error Profile for 1992 Corrected for Load Shifting

smaller than the 95 MW standard deviation of the error profile after load shifting extraction. A visual inspection of the error profile (Figure 5.5) did not reveal this additional evening peak demand. A correlation analysis between the error profile and the community profile (done in STATISTICA) confirmed that the electrification load was hidden in the noise. It appeared that the random error content in the model was too high to allow the resolution of the additional electrification load.

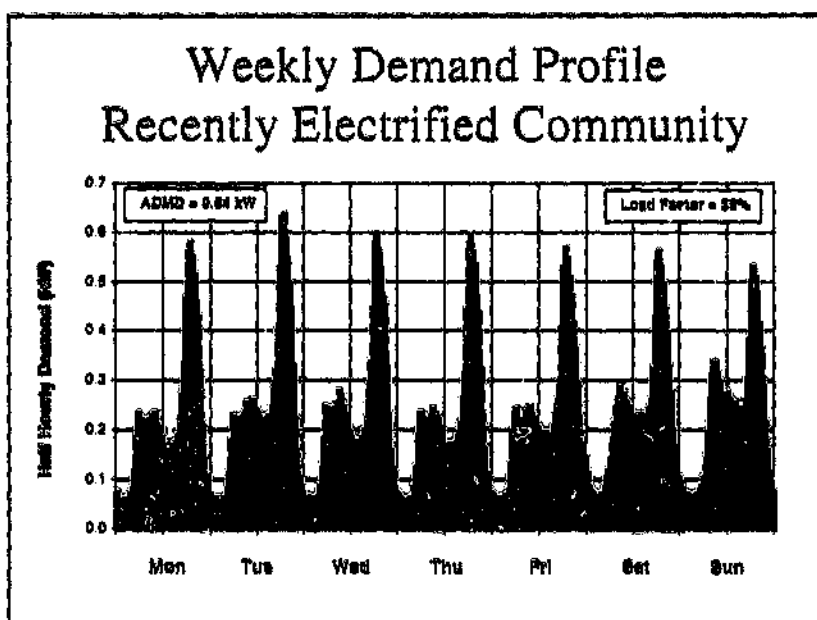


Figure 5.7 - Demand Profile of Recently Electrified Community

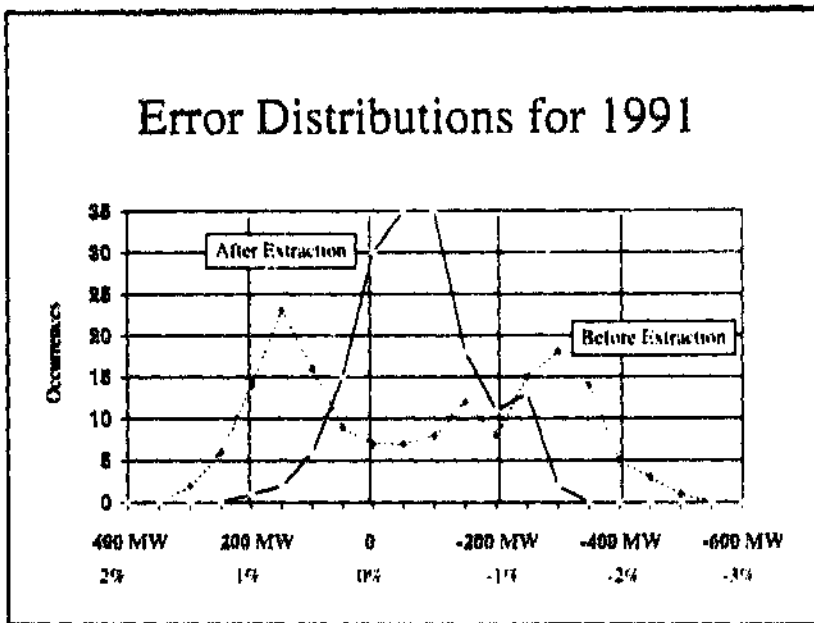


Figure 5.6 - Error Distributions for the 1991 Forecast

This implies an increase in Tariff E load shifting from 1990 to 1991 of about 370 MW.

If the model accounts for all loads, the error profile is expected to vary randomly, with a normal distribution and a mean value of zero. The 'quality' of the error profile can therefore be determined by a measure of the 'normalness' of the error profile. The Kurtosis of the uncorrected error profile was -1.4 while that of the corrected profile had improved to -0.188. Similarly, improving the error profile should result in a decreased standard deviation from the mean value. The uncorrected standard deviation was 212 MW, which was reduced to 95 MW after the load shifting correction. A plot of the error distribution (Figure 5.6) shows the bimodal shape before load shift correction, and the more normal shape after correction.

5.3.2 Measuring the Impact of Electrification in 1991

The weekly demand profile of a community electrified during 1991 is shown in Figure 5.7. This profile is typical for such communities and is characterised by the high and narrow evening peaks. The After Diversity Maximum Demand (ADMD) for this community was about 0.6 kW, which was also typical. Approximately 100 000 homes were electrified by Eskom between the winter of 1990 and that of 1991. The impact of the electrification program was thus expected to be identified as an unexplained additional evening peak demand of about 60 MW, and about 25 MW on the morning peak. Actual sales recorded to Eskom electrification customers in 1991 of about 15 GWh implied an evening peak impact of only about 5 MW. This was considerably

The additional load shifting evident had to be 'extracted' from the error profile. The average energy error was approximately zero (-136.9 MWh, or -0.005%), due to the model correction factor applied earlier. The Tariff E peak period error was positive by 15 543 MWh, or about 0.5%, and the off-peak period error was negative by 15 590 MWh.

A procedure was applied to the error profile, reducing the average peak period energy and increasing average off-peak energy by the same amount, to simulate the additional load shifting. This was done with a goal of minimising the average peak and off-peak errors. Reducing peak demand by 194.6 MW while increasing off-peak demand by 176.9 MW resulted in a minimum difference between the errors. This correction profile (Figure 5.4) was applied to the model error profile, resulting in the profile in Figure 5.5.

The correlation coefficient between the error profile of Figure 5.3 and the load shift profile of Figure 5.4 was -0.8897. This confirmed the large load shift component in the error profile. The correlation coefficient between the load shift profile and the error profile after the extraction procedure was applied (Figure 5.5), is 0.0265, which illustrates that the load shifting component has been successfully removed from the error profile.

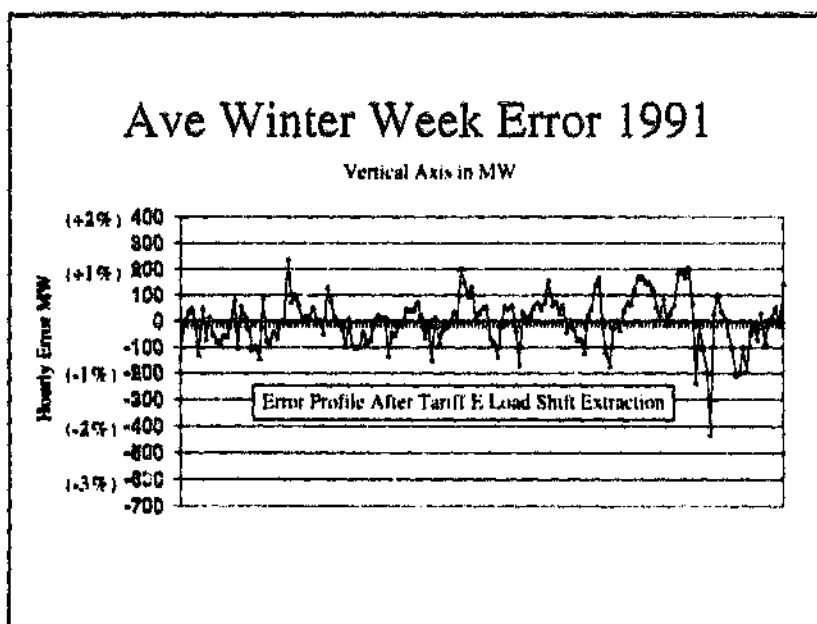


Figure 5.5 - Ave. Winter Week Error after Tariff E Correction

This indicates that additional load shifting by customers has occurred between the winter of 1990 (model base year) and 1991 (model forecast year).

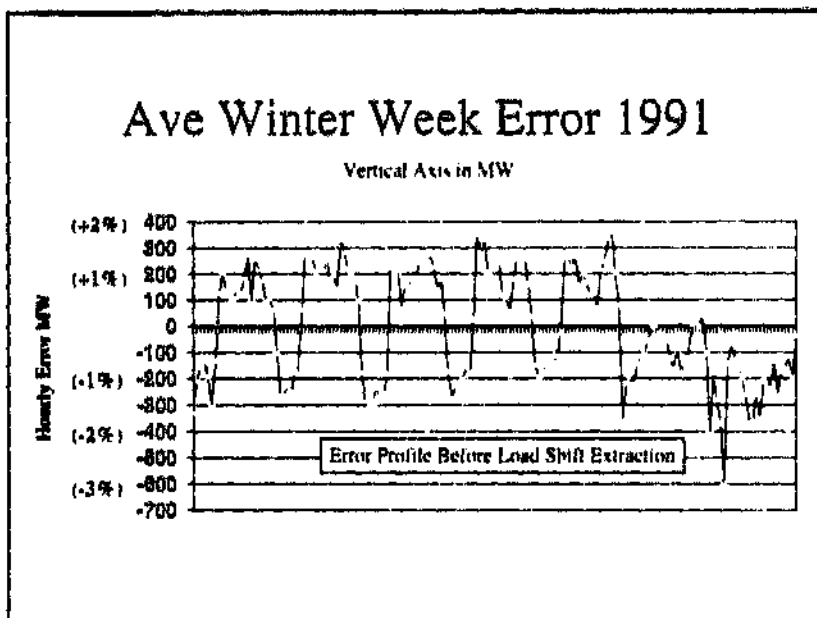


Figure 5.3 - Average Winter Week Error Profile for 1991

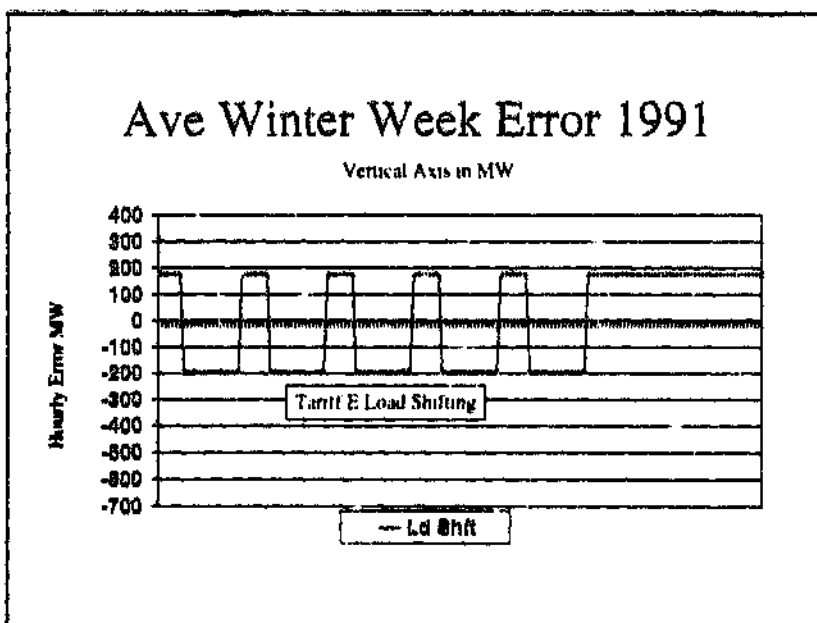


Figure 5.4 - The Tariff E Load Shifting Correction Profile

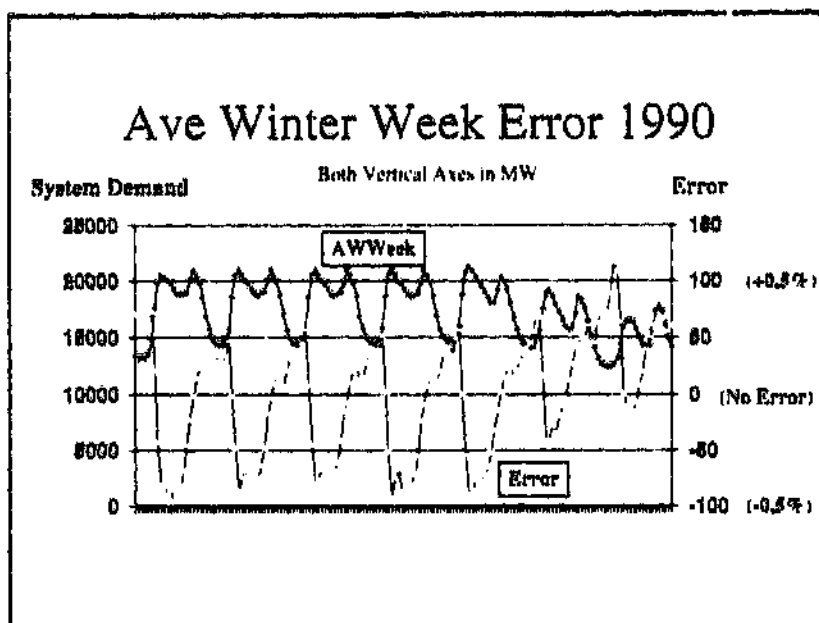


Figure 5.2- Average Winter Week Profile Error for 1990

The prototype XDFM overestimated the evening peak and underestimates the morning peak.

The maximum hourly errors were about 120 MW, and there is clearly a cyclic component with a period of one day present. The highest error of 120 MW represented about 0.5%, which was considered acceptable. The clear cyclic nature of the error profile suggested that the random component was very small indeed - certainly below 50 MW, or 0.25%. This implied that structural changes in the profile in the order of 50 MW to 100 MW should be discernible in the 1991 and 1992 forecasts.

Removing the 'bad' customers in the Other Mining and Other Industry classes, and consolidating the Mining and Industrial classes also appears to have improved the model accuracy, as it is considerably better than the original model described in Chapter 3.

5.3 TESTING THE FORECAST YEARS 1991 AND 1992

5.3.1 Measuring Additional Load Shifting in 1991

The AWWk error profile for 1991 is shown in Figure 5.3. The model clearly over-estimated Tariff E peak periods and under-estimated off-peak periods. (Tariff E has defined peak periods as 07h00 to 23h00 on weekdays, excluding public holidays.)

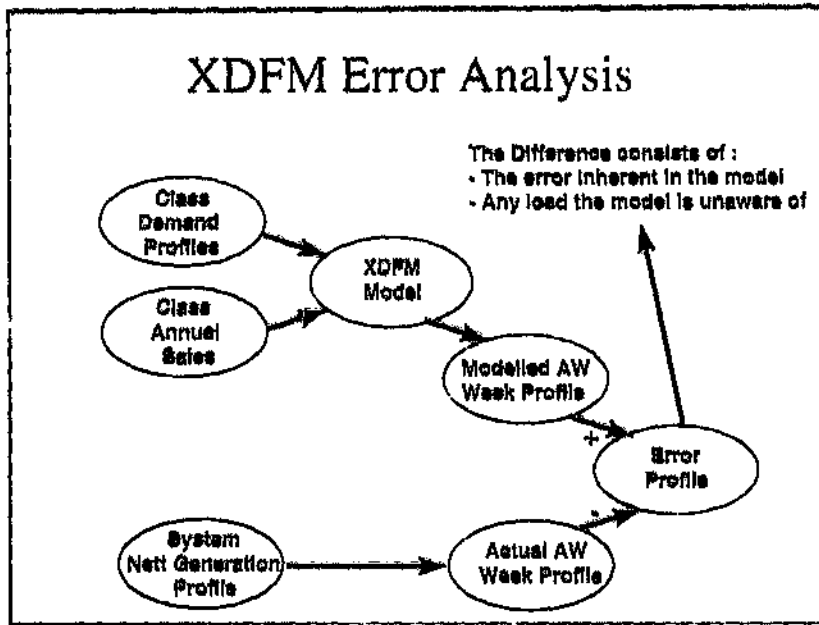


Figure 5.1 - The XDFM Error Analysis Process

5.2 TESTING THE BASE YEAR - 1990

The actual AWWk Net Sent Out profile was developed and compared to the modelled profile. The model was found to have slightly overestimated the energy content of the AWWk, and a factor of 0,9578 was applied to each hourly value to correct the modelled AWWk energy. The reason for this overestimation was not known at the time. The effect was to reduce the mean error of the AWWk model to almost zero, but permit evaluation of errors in the profile shape. The Mean Absolute Percentage Error (MAPE) was 0,26%, or 45MW - which is negligible. The standard deviation of the error was about 65 MW. The error profile is illustrated in Figure 5

Chapter 5 - Testing the Prototype XDFM Model

5.1 THE OBJECT AND METHOD OF THE TESTING PROCESS

The most important requirement was to determine whether the model could detect changes in the system demand profile shape. There were two load components that the modelled 1991 and 1992 forecasts were unaware of. These were increased load shifting by Tariff E customers, and the impact of the national electrification program. It was hoped to identify and quantify these components.

Testing the model consisted of two phases. The first was to test the base year modelled system demand profile against the actual AWWk profile for 1990. If the model was accurate enough, the forecast years 1991 and 1992 were to be tested.

5.1.1 The Test Method

The test method is shown below (Figure 5.1). The actual average winter week profile was subtracted from the modelled AWWk profile on an hour-by-hour basis to produce an 'error profile'. This can be expressed as follows:

$$e(t) = F(t) - A(t) \quad (5.1)$$

where :

$e(t)$ is the error at time t
 $F(t)$ is the modelled AWWk demand at time t
 $A(t)$ is the actual AWWk demand at time t

It was expected that this error profile would contain two components:

- A small random variation, representing the random error inherent the model
- Regular patterns or cyclical components, representing any load the model is representing incorrectly.

6.3 LONG TERM FORECASTING WITH XDFM

Long term forecasting with XDFM implied a set of winter week models for each year of the planning horizon. The GEP staff use a 25 year horizon, and implementing this in a single spreadsheet would have been impractical. The model was ported to Microsoft Excel as a workbook, with a separate worksheet for each winter model (Figure 6.1). The Excel XDFM model has been used for Eskom's long term forecasting process since 1994. The remainder of this chapter is essentially an extract from the Eskom Integrated Electricity Plan for 1996, Volume 2 [Berrisford 1996]. It describes the use of the model in generating demand profile forecasts, seasonal LDC forecasts, and annual MD and LF forecasts.

6.3.1 Demand Profile Forecast

The XDFM was used to forecast average weekly demand profiles for each season in the long term forecasting horizon (1996 to 2015). The model estimates the Eskom Integrated System Demand Profile including the impacts of tariff induced load shifting. The primary output is in the form of a modelled Average Winter Week profile and derived profiles for the other seasons, for each year until 2015. XDFM is a disaggregation based model ideally suited to long term demand profile forecasting (five to thirty years). The model uses as primary inputs the forecast annual energy sales per customer class [Prinsloo 1996] and weekly demand profiles for each customer class. Figures for Own Usage and Losses in the Transmission and Distribution networks are also incorporated.

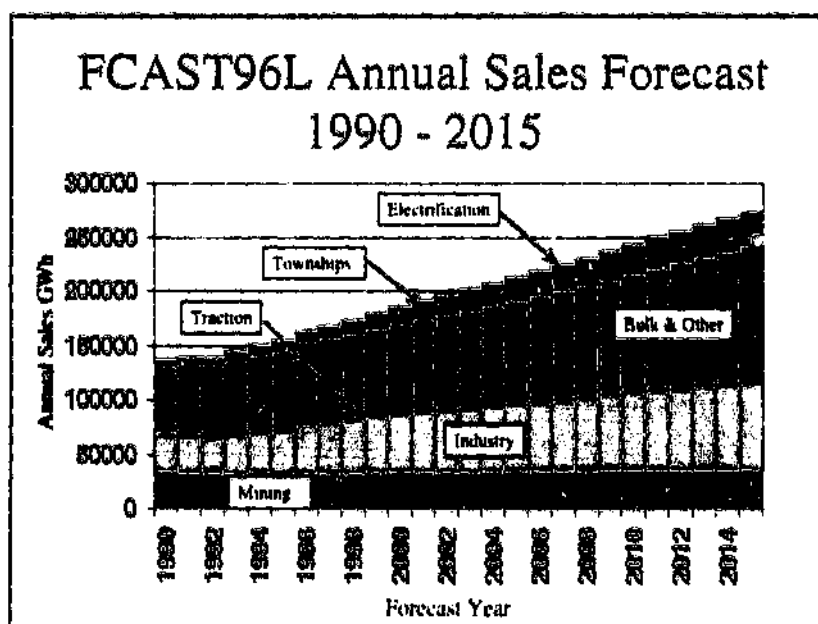


Figure 6.8 - Sectoral Energy Sales based on Moderate Forecast

6.2.1 The Tariff Impact sub-models in XDFM

Two tariff response sub-models were developed for the new XDFM, for Tariff E (Nightsave) and Tariff T (Whateverflex). These models both assumed pure load shifting in response to the tariffs. This implies that a customer's total energy consumption remained constant, although the demand increased during off-peak hours and decreased during peak periods.

Demand profiles from several Tariff E customers indicated that a responding customer would increase off-peak demand by approximately 10%, which implied a peak demand decrease of 11%. This is because there are 80 peak hours and 88 off-peak hours per week. This resulted in an effective shifting of 5.2% of consumption from peak to off-peak periods.

The shifted hourly demand for each class $L_i(t)$ was defined as:

$$L_i(t) = K_i(t) \cdot 1.1 \cdot E_i \quad (6.5)$$

for off-peak hours, and as:

$$L_i(t) = K_i(t) \cdot 0.89 \cdot E_i \quad (6.6)$$

for peak hours, with E_i being the estimated proportion of class sales that would shift load. The sub-model was implemented as an additional customer class demand profile shape which added demand during off-peak hours and reduced it during peak hours. This was implemented for both the Mining and the Industry classes separately.

A similar approach was adopted to model the Time-of-Use tariffs, and this was implemented for each of the Mining, Industrial, Traction, and Bulk&Other classes. The Tariff T profile shape is illustrated in Figure 6.4. The levels are relative to a 100% load factor shape, which would allocate 0,005952 kWh per week to each hour.

6.2.2 Testing the Load Shifting Sub-Models

These sub-models were then used to estimate the load shifting that had occurred in 1993 and 1994, using the same approach used to validate the prototype model. The error profile for the average winter week of 1993 is shown in Figure 6.5. The shape of the error profile indicates a large component of Tariff E load shifting. Introducing 500 MW of Tariff E load shifting with the sub-model results in the error profile of Figure 6.6. Note the improvement in the key statistics describing the error.

The resulting error profile still contains a pattern that indicates load shifting out of Tariff T peak times (weekdays 07h00 to 10h00 and 18h00 to 20h00). Applying 200 MW of Tariff T load shifting removed this pattern and further improved the key statistics (Figure 6.7). The MAPE was now 0.57%, the standard deviation is 133 MW. The kurtosis is 0.229 which indicates a fairly normal distribution of the 168 individual hourly errors.

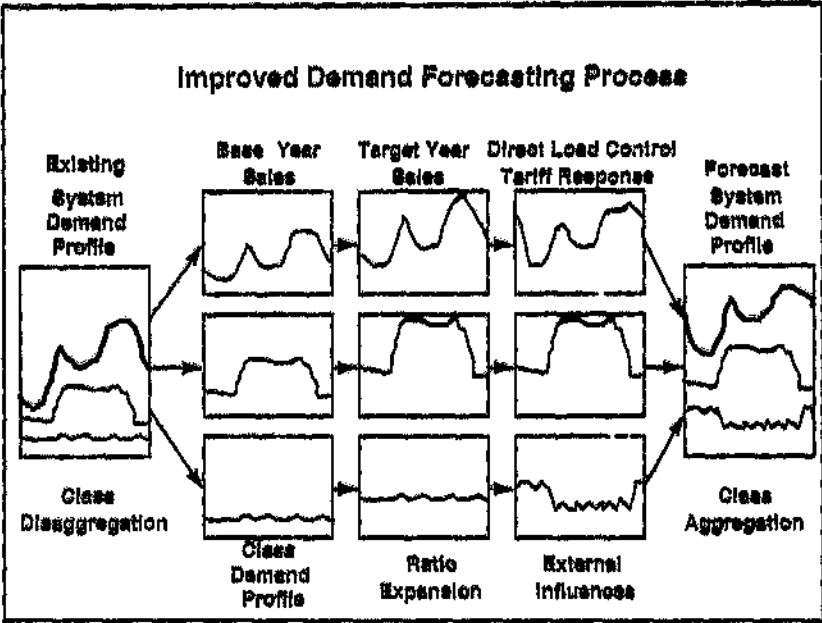


Figure 6.2 The Improved Demand Profile Forecasting Process

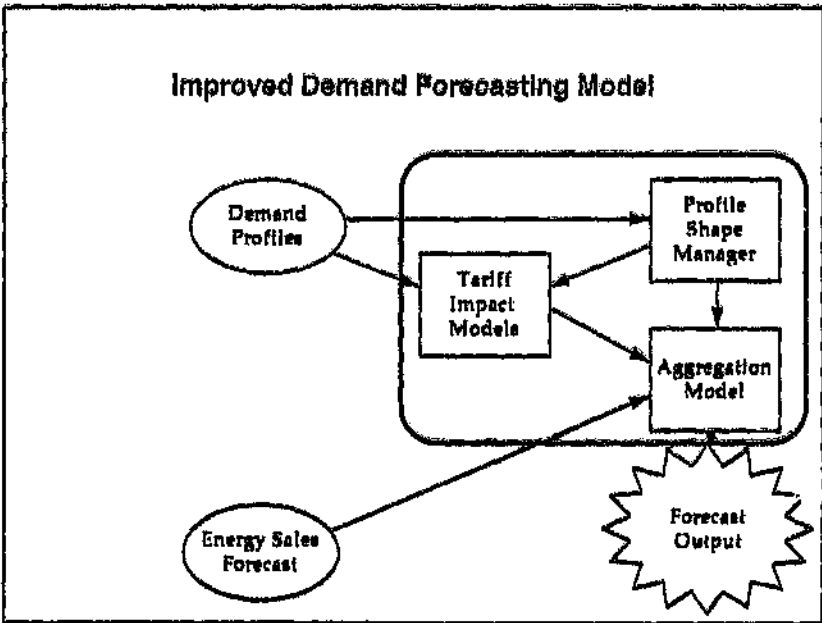


Figure 6.3 Improved Demand Profile Forecasting Model

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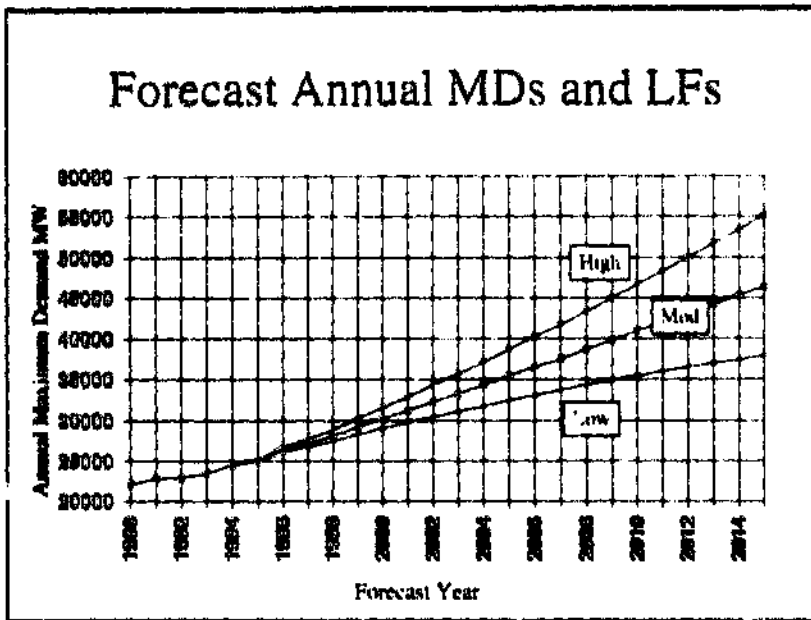


Figure 6.13 - Annual MDs for the Three Forecasts

The forecast figures are within 250 MW for four of the six years, with a worst case of 467 MW over-estimate in 1991 followed by a 371 MW under-estimate in 1994, which was mainly due to the extreme winter weather in that year.

The annual MDs thus derived from the XDPM model for the Moderate forecast were then scaled to provide annual MD figures for the Low and High growth forecasts. These are shown in Figure 6.13.

6.3.5 Probability Distribution of the XDPM Annual Peak Demand

The XDPM does not forecast annual MD directly, as this is affected by external influences such as weather. The annual MDs are therefore estimated by applying a factor to the AWW MD obtained from the model. The factor is derived from an analysis of the historical relationship between AWW MD and annual MD. This analysis indicated that the annual MD has a mean value of about 4% above the AWW MD, with a standard deviation of about 3% of the AWW MD. The actual distribution is not normal and obviously the annual MD cannot be lower than the AWW MD. The use of historical relationships is also suspect due to the annual MD changing from a morning peak to an evening peak in 1992. Since the system evening peak is more temperature sensitive than the morning peak, it is possible that the annual MDs will be slightly higher than those estimated in this forecast. The XDPM estimate for the 1996 annual MD was one of the inputs to the EDD 1996 annual MD forecast, described in a related report [van Harmelin 1996].

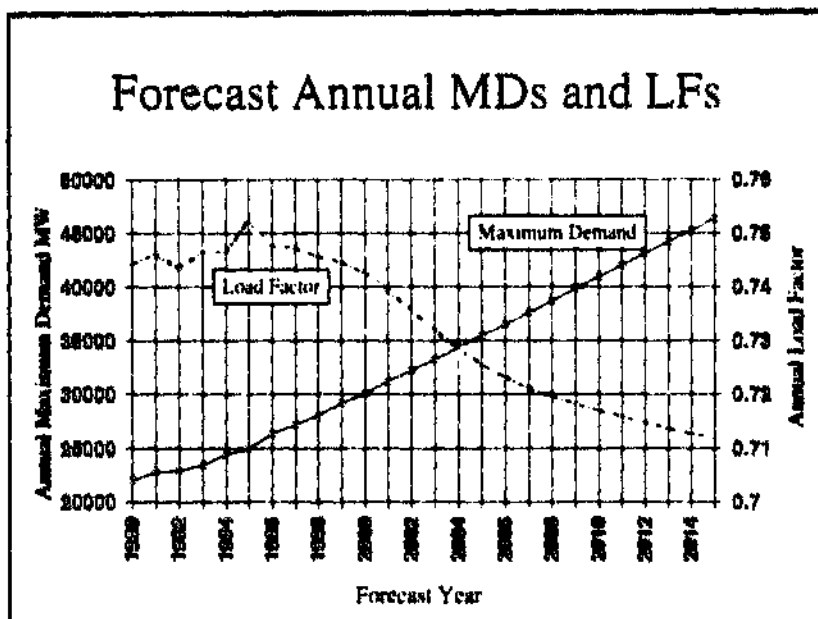


Figure 6.11 - Moderate Growth Forecast Annual MDs and Load Factors

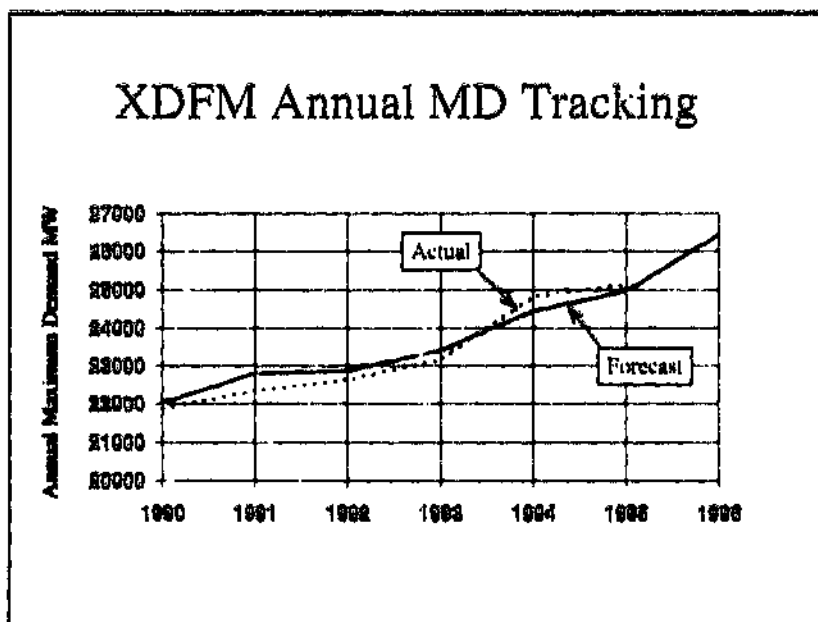


Figure 6.12 - Tracking of the Annual MD by the XDPM model

The accuracy of the XDPM model, with respect to forecast annual MD, is illustrated in Figure 6.12. Using actual sales figures for 1990 to 1995, the model was used to forecast the annual MDs for those years.

6.3.4 XDPM Annual Maximum Demand Forecast

Annual Maximum Demand (MD) is derived from the AWW profile. The MD is largely a function of the winter weather impact on the AWW profile. Since the XDPM does not include a weather impact model, the relationship between the AWW and the annual MD is based on historical figures since 1979. These indicate an annual MD that is an average of about 4% higher than the AWW MD, with a standard deviation of about 3% of the AWW MD. The annual Maximum Demands and Load Factors for the Moderate Growth forecast are tabulated below. The table includes the annual MDs and load factors produced by the XDPM for the NLS scenario in 1995 for comparative purposes.

| XDPM Moderate Forecast Annual Maximum Demands and Load Factors | | | | | |
|--|-----------|-----------|------------|------------|-------------|
| Year | MD (Base) | LF (Base) | MD (95NLS) | LF (95NLS) | MD (Actual) |
| | MW | % | MW | % | MW |
| 1990 | 22 023 | 74.4 | 22 037 | 74.4 | 21 863 |
| 1991 | 22 809 | 74.6 | 22 809 | 74.6 | 22 342 |
| 1992 | 22 875 | 74.3 | 22 600 | 75.2 | 22 640 |
| 1993 | 23 409 | 74.7 | 23 395 | 74.7 | 23 169 |
| 1994 | 24 437 | 74.7 | 24 435 | 74.7 | 24 808 |
| 1995 | 24 947 | 74.6 | 25 112 | 74.6 | 25 133 |
| 1996 | 26 436 | 74.8 | 26 611 | 74.8 | |
| 1997 | 27 172 | 74.7 | 27 469 | 74.8 | |
| 1998 | 28 060 | 74.6 | 28 301 | 74.6 | |
| 1999 | 29 173 | 74.5 | 29 287 | 74.5 | |
| 2000 | 30 140 | 74.3 | 30 260 | 74.3 | |
| 2001 | 31 197 | 73.9 | 31 234 | 73.9 | |
| 2002 | 32 240 | 73.6 | 32 178 | 73.6 | |
| 2003 | 33 263 | 73.2 | 33 158 | 73.2 | |
| 2004 | 34 298 | 72.9 | 34 181 | 72.9 | |
| 2005 | 35 396 | 72.6 | 35 171 | 72.6 | |
| 2010 | 40 911 | 71.7 | 39 986 | 71.4 | |
| 2015 | 46 337 | 71.2 | | | |

Table 6.2 Annual Maximum Demands and Load Factors for the Moderate Forecast

These figures are plotted below in Figure 6.11, along with the actual annual MD for 1990 through 1995. Note the long term decline expected for annual load factor, and the 1996 boost provided by completion of the Alusaf Hillside plant.

6.3.3 Seasonal Average Week Demand Profile Forecast

Statistical analysis of the system demand profile revealed three distinct 'seasons' within the year. These are weeks 1 to 22 (Prewinter), weeks 23 to 35 (Winter), and weeks 36 to 52 (Postwinter). Prewinter and Postwinter have similar shapes but different magnitudes, while Winter has a distinct shape as well as magnitude. The XDPM model forecasts the Average Winter Week (AWW) profile for each year, from which the average weekly demand profiles for the other seasons are derived. Figure 6.9 depicts the forecast AWW profiles for the Base Case scenario, for every fifth year from 1990 to 2015. The major impacts evident are a continuing growth of the evening peak relative to the morning peak, as well as an large increase in the daily demand swing, both responsible for the long term decline in annual load factor.

The average winter week demand profiles were then sorted to produce average winter week Load Duration Curves (LDCs). These were then ratiometrically scaled to produce average weekly LDCs for the other two seasons, as illustrated in Figure 6.10 for the year 2000. These are based on the historical average ratios between the average seasonal week LDCs for several years, resulting in two sets of 168 ratios. These profiles and LDCs are available in spreadsheet file F96LNLSG.XLS for the scenario described above.

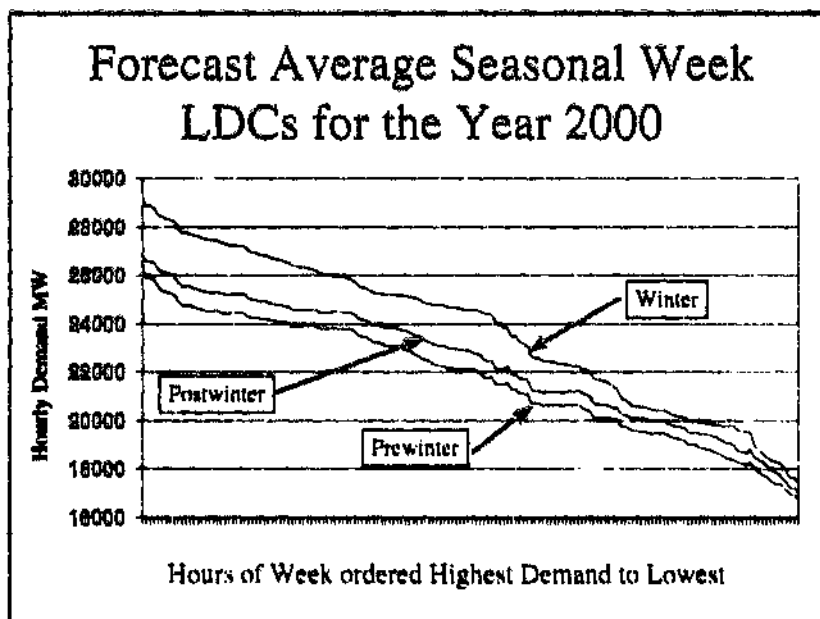


Figure 6.10 - Average Week LDCs for each Season for 2000

The sectoral energy sales forecast was done for the Moderate Growth forecast, and class sales figures for this forecast were used for the XDFM model. These figures, aggregated into the six classes used by XDFM, are illustrated in Figure 6.8.

6.3.2 Scenario modelled for the 1996 Demand Profile Forecast

The XDFM was used to forecast one load shifting scenario, called the Base Case. This scenario assumes that no *proportional increase in* load shifting by customers will take place. An analysis of the system demand profile and customer billing figures indicates that the expected additional tariff induced load shifting did not occur during 1993 and 1994. In fact, the impact of load shifting on the system demand profile actually decreased. This is a result of lost load shifting in the Ferrochrome industry and suspected reduction in load shifting in the gold mining sector, together with little additional response to Tariffs E (Nightsave) and T (Megaflex). The Base Case scenario assumes some further load shifting during 1996, with a gradual increase to the 1992 level (over a period of five years) and no proportional load shifting increase thereafter.

The Tariffs E (Nightsave) and T (Megaflex) models are incorporated into the XDFM model as demand profiles that increase hourly off-peak demands and increase peak demands by predefined ratios and to predetermined proportions of each class profile. The ratios are currently chosen such that the total class weekly energy remains constant and approximately 5.2% of the class energy (for the class proportion) is shifted from peak and standard times to off-peak periods. The figure of 5.2% was obtained from a study of available customer demand profiles and literature from overseas utilities.

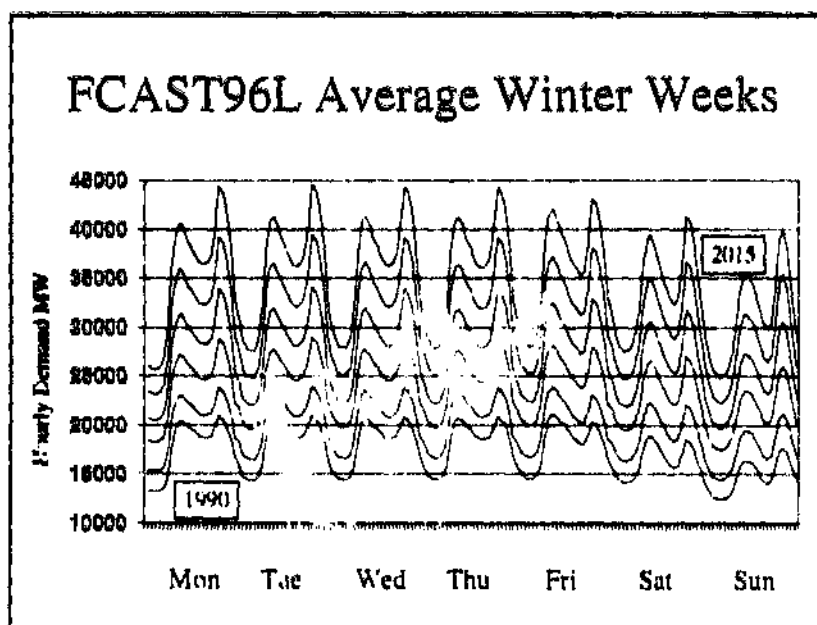


Figure 6.9 - Forecast Average Winter Week Demand Profiles

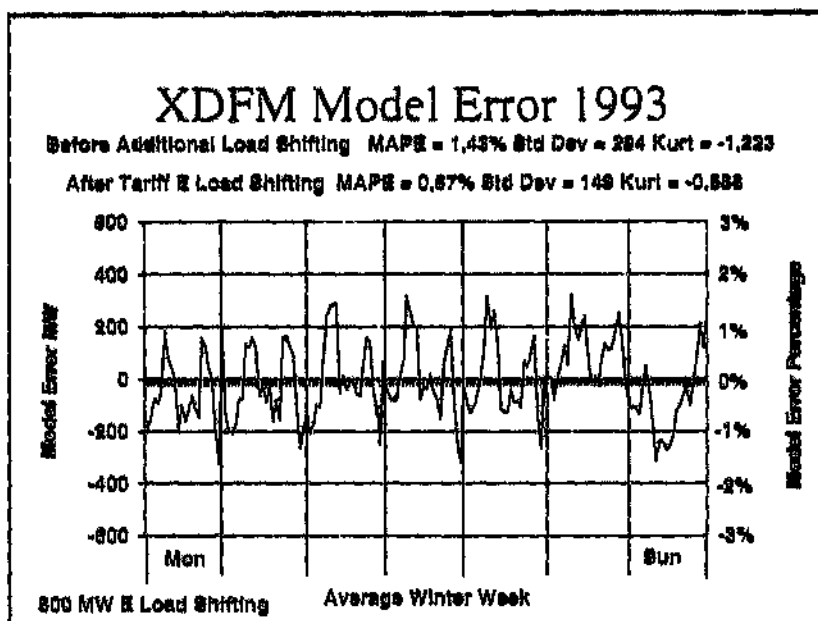


Figure 6.6 - 1993 Error Profile with Tariff E Load Shifting

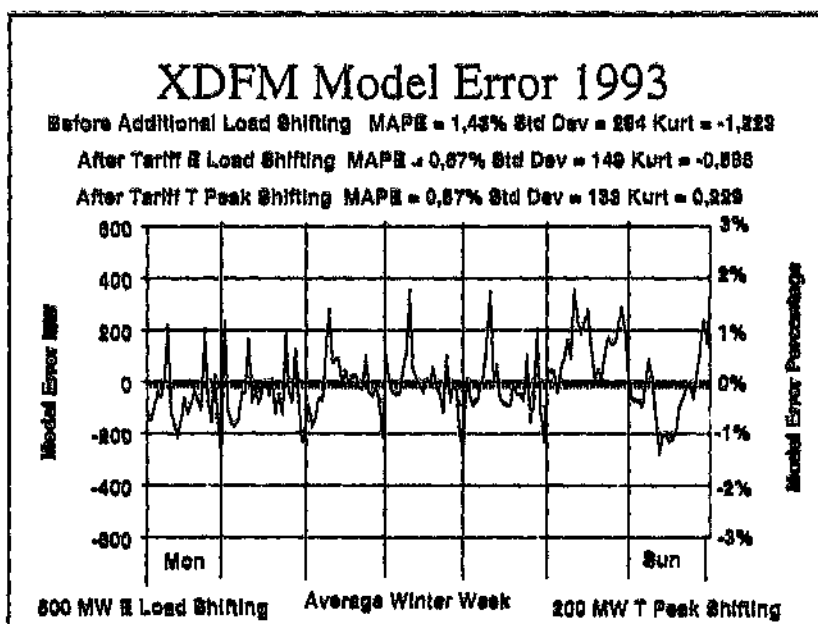


Figure 6.7 - 1993 Error Profile with Tariffs E and T Load Shifting

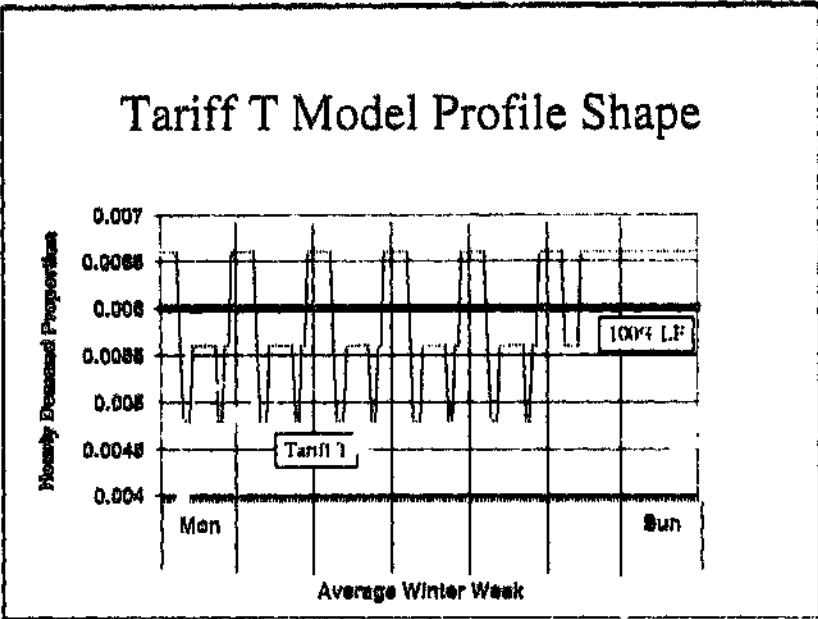


Figure 6.4 - Tariff T Profile Shape

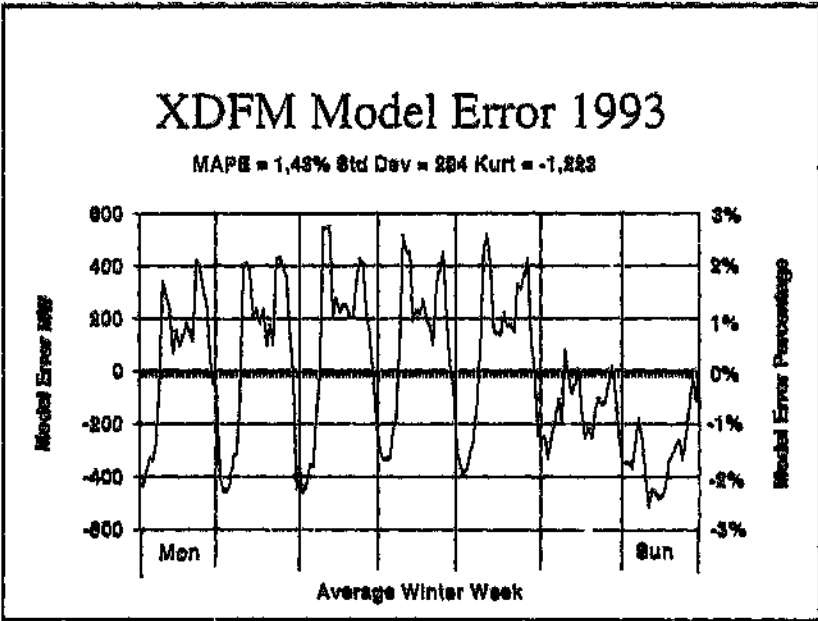


Figure 6.5 - XDPM Model Error 1993

hour (Equation 6.2). The actual AWWk demand is the sum of the modelled class demand and the model's error. This can be expressed as :

$$A(t) = \sum_{j=1}^m K_j(t) + \varepsilon(t) \quad (6.2)$$

Since the model is simply the sum of the class demands, the model error is actually the sum of the class errors.

$$A(t) = \sum_{j=1}^m (K_j(t) + \varepsilon_j(t)) \quad (6.3)$$

Each class demand is the product of an estimate from the class shapes and a SCF (ignoring the loss correction factor). If the SCF factors are not applied to calculate $K_j(t)$ then the error component $\varepsilon_j(t)$ includes the SCF factors for each class.

$$A(t) = \sum_{j=1}^m (K_j(t) \cdot \sigma_j(t)) + \varepsilon_j(t) \quad (6.4)$$

If one assumes that the SCF is unknown but consistent for all hours and the sum of the class demands equals the known actual AWWk demand, then the 168 models represent a set of simultaneous equations. Any five can be solved to obtain the SCF factors for the five classes. Several sets of five hours were solved and the resulting SCF factors averaged.

These additional estimates for the SCF figures proved more accurate than those used in the prototype model.

6.2 MODELLING TARIFF IMPACTS

To be useful, the forecasting model must be able to incorporate the impacts of the external influences. Since these may affect the classes differently, these impacts must be estimated for each class independently. An improved disaggregation based demand profile forecasting process is depicted in Figure 6.2.

The 1993 model was enhanced to incorporate several new features, including Tariff E and T impact estimators, for the IEP Committee in 1994. This improved model can be shown diagrammatically as Figure 6.3. The components within the rectangle were implemented as a number of spreadsheets.

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