



SCHOOL FOR MECHANICAL AND
MATERIAL ENGINEERING

The use of neural networks to determine the
long-term impact of
demand side management.

by

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2003



The use of neural networks to determine the long-term impact of demand side management.



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B-Eng. (Mech.) PU for CHE

Submitted in fulfilment of the requirements

for the degree Magisterial in Engineering

in the School of Mechanical and Material Engineering at the

Potchefstroom University for Christian Higher education,

Potchefstroom

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Potchefstroom

November 2003



ACKNOWLEDGEMENTS

The writer of this dissertation wishes to thank the following people:

- Prof L.J. Grobler for his excellent guidance, advice, patience and encouragements during this time. It has been an honour and privilege to learn so much from a man with such a high level of expertise.
- The personnel of the Potchefstroom University for Christian Higher education, for their support over the many years of study.
- Prof G.J. Delport and his team at the Centres for New Energy Studies at the University of Pretoria, for their assistance in the data collection from the database. Without the hourly data I have received from them, this project would not have been possible.
- Eskom, for the funding of this project.
- My parents, family and friends, for their constant support, encouragement and patience during these three years of study. It was a privilege to have such friends, who were always there in time of need and laughter.
- My Heavenly Father, who has placed me in South Africa and whose guidance, protection, provision and love I experienced every single day of this study.



ABSTRACT

Title : The use of neural networks to determine the long-term impact of demand side management.

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Eskom, South Africa national electricity provider, estimates that in the year 2006 South Africa will experience a capacity shortage. One way to address this problem is through the implementation of Demand-Side Management (DSM) in various sectors, ranging from the commercial to the industrial. For Eskom to succeed in their vision of implementing DSM, a tool has to be developed that can illustrate the long-term impact of various DSM options for a region. This tool could then be used to illustrate the various role players the advantages of implementing DSM.

The purpose of this study was to test if Neural Networks (NN's) can be applied in the construction of an hourly baseline for a region. This baseline could then be used to illustrate the Long-term impact of various DSM options.

In this study a technique was developed using hourly data to construct a baseline model for the calculation of the long-term impact of DSM. This technique was then tested and evaluated on a case study.

To achieve this goal, an investigation was launched to determine which inputs have an influence on the energy use of a region. The different variables that influence the neural network topology were also investigated.

This information was then used to develop a technique that models the energy use of the area. To determine accuracy of the simulated energy use, a verification procedure was developed based on an internationally accepted verification model, using data the NN did not "learn" on. Sufficient accurate results were obtained



using the defined indices. Thus NN can be used to model the energy use of a region.

The major disadvantage of this technique is that hourly data for the whole year was used to train the model on. The question arises into just how much information is needed to model the NN. Subsequently an investigation was launched to determine the minimum data set needed to model the energy use.

It was found that a full factorial data set is the minimum set of data that a NN needs to train on. In choosing this data, a study has to be conducted on previous data to determine exactly when the best combination could be obtained. The results indicated that the data could not be minimised due to the configuration of input data.

For this study, the months of the year were encoded. This aided the NN in learning the relationship between the various inputs and the energy use. It was found that this is a crucial step in aiding the NN. Thus the NN could not simulate accurate enough results without the encoded data. This results that the number of months cannot be minimised with the current technique used.

The model then can be used to evaluate different DSM options by subtracting the hourly differences from the baseline. This information is then used to evaluate the options using various indices. The indices included monthly energy use, maximum demand, the energy use during the various time of use periods and the impact of greenhouse gasses. The concept was illustrated by an actual case study.

The use of NN for modelling the baseline for the forecasting of the long-term impact of DSM is considerable faster than current techniques with a timesaving element of up to 90 %.

The use of NN is thus a viable technique to model the baseline. The results indicate that NN can successfully be used for cases with a high diversity in the load, and with little or no knowledge of the underlying systems.



OPSOMMING

Titel : Die gebruik van neurale netwerke om die langtermyn impak van aanvraag bestuur te bereken.

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Skool : Meganiese en Materiaal Ingenieurswese.

Graad : Meestersgraad in Ingenieurswese.

Eskom, Suid Afrika se nasionale elektrisiteit voorsiener voorspel dat Suid Afrika teen die jaar 2006 'n tekort aan elektrisiteit gaan hê. 'n Manier om die huidige probleem aan te spreek is deur die implementering van aanvraag bestuur in verskeie sektore. Vir Eskom om suksesvol te wees in hul visie om aanvraag bestuur te implementeer, moet 'n prosedure geskryf. Die prosedure moet dan die impak van aanvraag bestuur vir die onderskeie rol spelers kan illustreer.

Die doel van die studie was om te toets of neurale netwerke suksesvol gebruik kan word om 'n uurlikse basislyn te konstrueer. Die basislyn kan dan gebruik word om die langtermyn impak van aanvraag bestuur op 'n streek te illustreer.

Tydens hierdie studie is 'n metodologie ontwikkel vir die konstruksie van 'n uurlikse basislyn met die hulp van neurale netwerke. Die metodologie is getoets en geëvalueer vir 'n gevallestudie.

Vir die doel, is 'n ondersoek gedoen om te bepaal watter faktore die energieverbruik van 'n streek beïnvloed. Verder, is die invloed van die neurale netwerk se opstelling ook ondersoek.

'n Verifikasie prosedure is ontwikkel om te verseker dat die basislyn wat gesimuleer is, wel 'n akkurate voorstelling van die werklik data is, al dan nie. Die prosedure is gebaseer op 'n internasionale aanvaarde prosedure. Om te verseker dat die model wel die energieverbruik akkuraat kan simuleer, is 'n aparte stel data gebruik. Tydens die ondersoek is daar 'n simulاسie ontwikkel wat aan al die voorafopgestelde vereistes voldoen.



Die nadeel van die tegniek is dat dit 'n volle jaar se uurlikse data benodig word om die energieverbruik suksesvol te kan simuleer. Die vraag ontstaan wat die minimum data is wat benodig word om die energieverbruik van 'n streek suksesvol te kan simuleer.

Dit is bevind dat die minimum data stel, ten minste al die kombinasies van die belangrikste insette wat 'n impak het op die energieverbruik moet hê. Vir dit moet 'n studie gedoen word om te bepaal wanneer die beste kombinasie van data punte versamel moet word.

Gedurende die studie, is die maande se data gekodeer, sodat die neurale netwerk die verband tussen die inset en uitset makliker kan vind. Dit is bevind dat die stap 'n belangrike sleutel was om die neurale netwerk te help. Dus kon die neurale netwerk sonder die enkodeerde maande nie akkuraat genoeg simulatie moduleer nie. Dienooreenkomstig kan die aantal maande nie verminder word nie met die tegniek wat gebruik is.

Die gesimuleerde energieverbruik is dan gebruik om die langtermyn impak van die verskeie aanvraag bestuur opsies te evalueer, deur gebruik te maak van verskeie indekse. Die indekse het onder andere ingesluit die maandelikse energieverbruik, die maksimum aanvraag, die jaarlikse besparings, die besparings vir die verskeie tye volgens TOU ens. 'n Gevalle studie is gebruik om die impak op die uurlikse energieverbruik te illustreer.

Die gebruik van neurale netwerke in die moderering van 'n basislyn is ongeveer 90% vinniger as die tradisionele tegnieke. Die gebruik van neurale netwerke is 'n lewensvatbare tegniek om die energieverbruik van 'n streek met 'n hoë diversiteit en min kennis van die onderliggende stelsels te simuleer. Die basislyn kan dan gebruik word om die langtermyn impak van aanvraag bestuur te illustreer.



CONTRIBUTION OF THIS STUDY

The contributions of this study are as follows:

- Eskom, South Africa's national electricity provider currently facing numerous problems concerning the energy profile of South Africa. A solution to the problem is, the implementing of Demand Side Management (DSM) in various segments. However, the past as shown that DSM did not penetrate the market as rapidly as expected. A literature survey was conducted into the slow market penetration.
- To understand the full impact of DSM, a literature survey was conducted on what DSM is and the various ways DSM could be implemented in the commercial sector.
- A literature survey was conducted of the various techniques currently used to establish a baseline. The various advantages and disadvantages were investigated of the current techniques used.
- A literature survey was conducted on Neural Networks. A broad overview was given on NN, focussing on their background, basics and relationship to statistical methods.
- A new simulation approach was developed for the establishment of a baseline with the aid of NN. This simulation approach included weather and non-weather related variables.
- A technique of using NN to establish a baseline was applied on a case study to test its practical application. It was determined the NN could successfully be used to establish a baseline.
- A computer application was developed that use the baseline to illustrate the impact of various DSM options. The computer application can become a handy tool to determine:
 - Which type of programme to promote with DSM (ex. Higher efficiency in lighting versus higher efficiency in water heating devices) showing which one to use with the largest impact to cost.
 - Whether it would be economical for Eskom to promote DSM procedures and strategies or to upgrade the current installed system, especially for fast growing areas, such as the Midrand area in the Gauteng province



- The computer application could be used to illustrate the:
 - The commercial benefits and electricity savings by the application of DSM strategies and procedures to building owners and tenants, architects and engineers and other stakeholder;
 - The financial benefits of applying DSM. This will encourage property stakeholders to accept DSM and apply it as part of planning and construction as well as the operation of a building.

As DSM penetrates the market much faster. The effect of DSM include:

- The reduction in the peak generation of Eskom;
- The reduction in the electricity price;
- The reduction in carbon dioxide emissions (green house effect) and
- The stimulation of the economy of our country.

It can be concluded that the effect of the project, will start on a small scale, but as DSM grows, a major effect can be felt on the economy of South Africa.

ARTICLES AND CONFERENCE PAPERS EMANATING FROM THIS STUDY

From this study the following papers emanated:

- One conference paper was presented at the 9th International Conference on Domestic use of energy held Cape Town South Africa in April of 2001.
 - W.H. Kaiser and L.J Grobler: The use of Artificial Intelligence to baseline the energy use of a Campus, *Proceedings of the 9th International Conference on the Domestic use of energy*, pp 307
- One article was accepted and published in Journal of Energy in Southern Africa:
 - W.H. Kaiser and L.J. Grobler: The use of Neural Networks to baseline the energy use of a campus, *Journal of Energy in Southern Africa*, Vol 13 No. 1 February 2002, pp 1 -13



NOMENCLATURE

Abbreviations

AHU	Air handling unit
CCG	Conventional Control Gear
CFL	Compact Fluorescents Lamps
CPUC	California Public Utilities Commission
CV(RMSE)	Coefficient of Variation on the Root Mean Square Error
DSM	Demand Side Management
ECG	Electronic Control Gear
ECMS	Energy Management and Control System
ESCOs	Energy Service Companies
ERR	Error
GP	Genetic Programming
GA	Genetic Algorithm
HVAC	Heating Ventilation and Air-Conditioning
HID	High Intensity Discharge
HPS	High Pressure Sodium
IEP	Integrated Electricity Planning
IRR	Internal Rate of Return
LNSPC	Large Non-Residential Standard Performance Contract
LPS	Low Pressure Sodium
MBE	Mean Bias Error
MH	Metal Halide
MLE	Multi Likelihood Estimator
MLP	Multi Layer Perceptron
NN	Neural Network
NN's	Neural Networks
NPV	Net Present Value
OECD	Organisation Of Economic Corporation Development
RNN	Recurrent Neural Network
TSD	Thermal Storage Devices
VSD	Variable Speed Drive
TOU	Time Of Use



Mathematical Symbols

w_i	Numerical weight
x_i	Input data
y_i	Final value
f_i	Transfer function
N	Number
M	Measured data
S	Simulated data



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1 Introduction

1.1 Introduction

John Sculley once said: "The future belongs to those who see possibilities before they become obvious."

Eskom, South-Africa's national electricity provider, estimates that the current demand in South Africa of approximately 2.5 %, will result in a peaking capacity shortage around 2006 and 2007 (Friedland, 2002), as illustrated in figure 1-1 below.

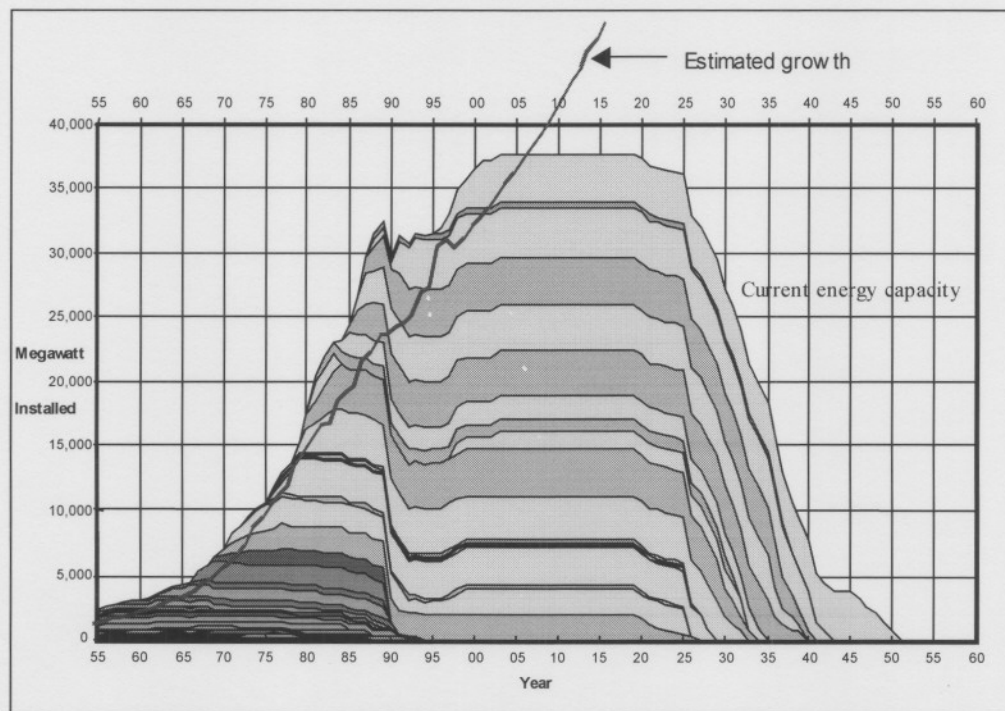


Figure 1-1: Projected generating capability of Eskom

Although South Africa has a surplus generation capacity, the lead times for new electricity generating plants are time consuming and they are very costly. For example the estimated lead times for coal-fired plants are around ten years and associated costs reach up to ten billion Rand. A decision to extend the current generation capacity must therefore be taken by 2002.

Furthermore, South Africa has an extremely energy intensive economy, with a high dependence on the mining and base metals industries. The growth of

electricity sales have been consistently higher than the Gross Domestic Product (GDP), reflecting the energy intensive nature of the economy (Eskom, 2001).

In addition, the South-African economy has energy intensity levels that are comparable to those in central Europe. These are up to five times higher than those of most of the Organisation of Economic Corporation Development (OECD) nations.

Other problems facing Eskom are the exhaustion of natural resources in the near future and wasteful use of limited fresh water supply.

Therefore, Eskom, South Africa's national electricity provider requires ways to alleviate the current problematic situation. One way to address the problem is by implementing Demand Side Management (DSM) and procedures in various areas.

1.2 What is DSM?

DSM activities are those activities, which involve action on the demand. Thus, they involve the customer side of the electric meter, either directly caused or indirectly stimulated by the utility. One common thread behind DSM activities is that it involves a deliberate intervention in the marketplace so as to change the configuration or magnitude of the load shape. DSM refers to a new approach to assist utilities in maintaining a balance between electricity supply and demand in today's uncertain planning climate (Gelling, 2:1993).

In South Africa, DSM is still a relatively new concept to most. While Eskom formally recognised DSM in 1992 when the Integrated Electricity Planning (IEP) was first introduced, the first DSM plan was only produced in 1994. In this plan, the role of DSM was established and a wide range of DSM opportunities and alternatives available to Eskom were identified (Eskom, 2001).

If DSM could be implemented to limit the residential demand growth, or mitigate the impacts through the provision of incentives for industry or commerce to move electricity load out of the peak periods, substantial benefits for all customer groups could be attained. Consequently, high price increases could be avoided through



4.3.2 Multi layer perceptrons

NN's consists of many interconnected neurons or nodes. The processing nodes are usually divided into disjoint subsets, also known as a layer, in which the nodes have similar computational characteristics

A distinction is made between the input, hidden and output layers, depending on their relation to the information environment of the NN's. The input layers from the first layer, that receives the inputs from the various input data points (Nelson & Illingworth, 1991:50). The network's output is generated from the output layer.

Any other layer is called a hidden layer, because they are internal to the network and have no direct contact with the external environment. The use of hidden layers allows the NN network to deal robustly with inherently non-linear or complex problems (Medsker *et al.*, 1994:168). Figure 4-4 illustrates this concept.

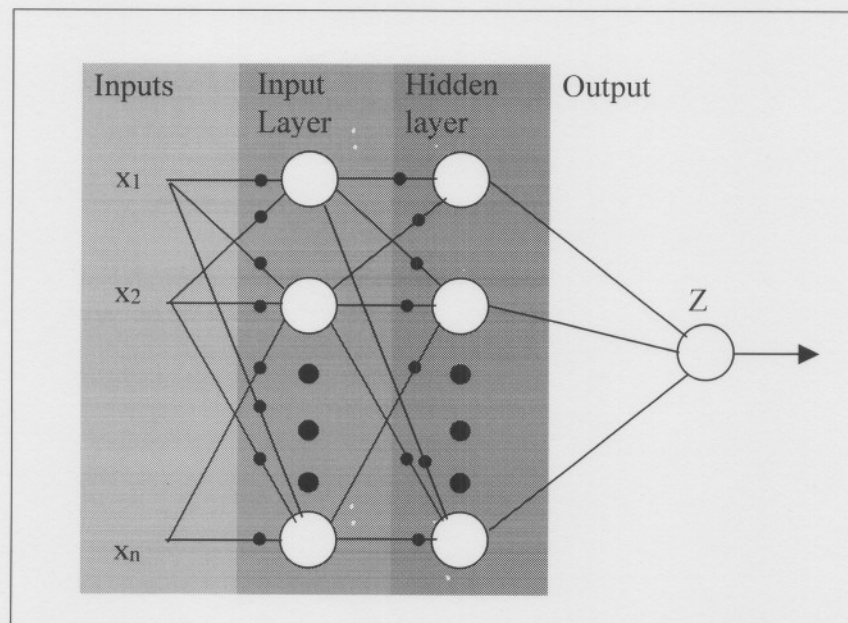


Figure 4-4: Structure of a typical multiplayer NN

The nodes on a particular layer are linked to other nodes in successive layers by means of weighted connections (Aldrich, 2000:18) as discussed for a single neuron.

the deferment and probable avoidance of certain generation capacity constructions (Eskom, 2001).

Eskom plans to save 7 300 MW using DSM over the next decade and a half. Interruptible load agreements are currently in place for 1 850 MW, while this could increase to 3200 MW by 2015. Electricity efficiency measures should account for a saving of 2500 MW and load shifting will account for the savings of another 1 600 MW (Africa Energy, 2002)

A DSM goal was set for the year 2002 on the Industrial Commercial Energy Efficiency (ICEE) sector to reduce Peak demand by 95 MW with a budget of R208 million (Eskom, 2001).

For Eskom to achieve this goal, a tool has to be developed to forecast the hourly long-term impact of DSM in a region. Currently there is a considerable need in the electricity industry for the ability to forecast the effects of DSM over time (Gellings, 1993:395).

The next paragraph will shed some light on why there is such a need to illustrate the long-term hourly impact of DSM on region.

1.3 The need for illustrating the long-term impact of DSM in a in a region.

For Eskom to succeed in their vision of implementing DSM, commercial building owners and tenants as well as the industry have to undergo a mind shift to accept DSM. In the past, DSM did not penetrate the market as rapidly as expected, indicating the need to illustrate to the various stakeholders the advantages of DSM. The aim of this section is to highlight some of the reasons for the slow market penetration.

Eskom traditionally has a low electricity prices and is ranked as one of the most inexpensive electric utility providers in the world, as is illustrated in Figure 1-2. A low electricity prices does not encourage customers to implement efficiency improvements, even though these electricity efficiency improvements may be extremely important to society at large (Reddy, 1991:953).



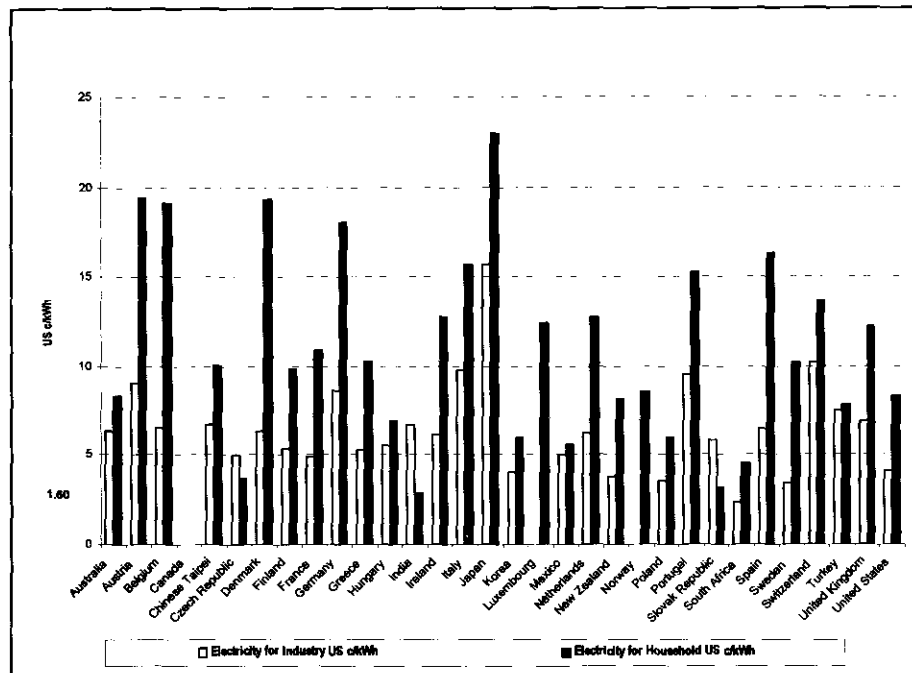


Figure 1-2: Utility price for electricity for different countries

An additional barrier in preventing market penetration is the ignorance of consumers with regard to the possible cost benefits, and the possibilities of DSM measures (Reddy, 1991:953).

End user costs savings are not significant enough, due to the high investment cost associated with electricity savings. This causes that these devices are not economically viable. The main reason for this is, that the greater the energy efficiency, the higher the cost (Reddy, 1991:953).

The cost and benefits of energy-efficiency improvements depend to a large extent on the current and future prices of energy. If there is uncertainty regarding these prices, consumers postpone their decisions to a later stage, when it is more viable (Reddy, 1991:954), or simply invest the money elsewhere.

There is also a consumer category who is knowledgeable, able to afford the efficient improvements and who is motivated but nevertheless helpless in identifying the associated devices and equipment that are the best options for their specific application (Reddy, 1991:954).

Finally, there is a consumer category that qualifies on all accounts – but is in the unfortunate situation of having an inherent inefficient facility. These consumers are victims of indirect purchase decisions. The most common example is that of tenants who are renting an energy inefficient facility. This problem stems from split burdens, namely that of the capital investment that falls on the landlord and the payment of the electricity bills that fall on the tenants (Reddy, 1991:955).

A possible solution to the various problems concerning energy efficiency and DSM inability to penetrate the market rapidly is to explain to the various stakeholders the advantages of implementing DSM.

For this, a tool that demonstrates the hourly impact of DSM for a region has to be developed. This tool could also be used to determine whether it would be more economical to expand the distribution network, with added transformers and power line, or to employ DSM strategies and procedures for the specific region.

Currently, no such tool exists that demonstrates the long-term impact of DSM in a region. The majority of long-term forecasting techniques found, are focused on forecasting the long-term effect of electricity of a area for example the forecasting of the electricity use on a national level, using economic indicators such as gross domestic product, and so on.

1.4 Objective of this study

The objective of this study is to develop and test a methodology in modelling an hourly baseline for determining the long-term effect of DSM in a region, focussing mainly on commercial activities.

The result of the methodology has to be of such a nature that it can:

- Provide an accurate projection of the hourly impact of DSM on a region using hourly data for the baseline.
- Provide a diagnostic indicator to evaluate the different DSM option for a ten-year life cycle, using various indices for example particle emissions, electricity savings and cost savings.



In order to achieve this, the following objectives need first be done:

- An investigation of what DSM is, what DSM is comprised of and how it can be implemented in the commercial sector.
- A literature survey of current work done on the construction of a baseline for a region. The literature survey was conducted to obtain information on what has been done up to date in this field as well as to establish where the various advantages and disadvantages of the current techniques lie.
- An investigation of what NN's are, to understand how it can be used and implemented in this dissertation. The investigation focuses on the basics of a NN and the main factors influencing the outcome of a NN.
- An investigation into the main factors influencing the electricity use of the various buildings in a region. This involves a clear understanding of the main factors to determine which factors have to be used in the simulation.
- The development of a sound simulation technique using the gained knowledge from the previous points.
- The development of technique to calculate the long-term hourly impact of the different DSM options, using the constructed baseline.

1.5 Overview of research

The dissertation is divided into 10 chapters. In each chapter the following is discussed.

Chapter 1: Background to the motivation for this dissertation.

Chapter 2 A literature study was conducted. More specific, information is provided on what DSM is, commonly used DSM techniques and three case studies of actual DSM strategies that have been implemented in South-Africa.

Chapter 3: A discussion of the current techniques used to construct a baseline, focussing on the advantages and disadvantages of the techniques.

Chapter 4: A brief description of Neural Networks (NN's), giving insight into what NN's are, their limitations and where they can be used. Secondly, a brief discussion of various studies aimed at forecasting the electricity use of a region.



No information was found that suggest that the use of NN for the establishment of a hourly baseline.

Chapter 5: The methodology used to forecast the long-term effect of DSM management in a region using hourly data.

Chapter 6: An introduction of the case study, explaining the applications of the various buildings for the region and the electrical network.

Chapter 7: A summary of the most important results that were obtained for the case study using NN for the case of using annual hourly data.

Chapter 8: Hourly annual data is not always available for a specific region. Thus, once it has been established that NN can be used to model the electricity use of a region, a study is undertaken to determine what the minimum data requirement is, in using NN for the construction of a baseline.

Chapter 9: The constructed of an hourly baseline is then used to determine the long-term impact of DSM in the case study, by evaluating two DSM options.

Chapter 10: A summary of the entire investigation is given, with conclusions and recommendations.

1.6 Impact of this study

After completion of this study a computer application and technique will be available for the long term forecasting of DSM in a region. The computer application will become a handy tool to determine:

- Which type of program to promote with DSM (e.g. higher efficiency in lighting versus higher efficiency in water heating devices) indicating which one to use with the largest impact to cost.
- Whether it would be more economically viable for Eskom to install DSM procedures and strategies or to construct a new substation which implies high installation costs, for a fast growing area such as Midrand in Gauteng.

The application could demonstrate the commercial benefits and electricity savings to building owners and tenants, architects and engineers through the application of DSM strategies and procedures.

The demonstrations of the financial benefits of applying DSM will encourage property stakeholders to accept DSM and apply it as part of planning and construction as well as the operation of a building. The effects of this are:

- Minimising the fluctuations in demand that Eskom is currently experiencing.
- Delaying the estimated peaking shortage predicted for South Africa.
- Decreasing the energy usage per GDP for South Africa, and making it more competitive in the world market.
- The reduction of the peak load generation of Eskom. This causes a rippling effect on the price of electricity, our natural resources, carbon dioxide emissions (green house effect) and the economy of our country.

It can be concluded that the secondary effect of the project will initially be minimal, but as DSM grows, a major effect can be expected on the economy of South Africa.

1.7 Summary

This chapter focused on the current situation that Eskom South-Africa's National electricity provider is facing. A possible solution to address the problem is through the implementation of DSM. Unfortunately DSM did not penetrate the market as rapid as expected.

Consequently, Eskom needs a tool to quantify the long-term hourly impact of DSM in an area. This tool could determine whether DSM is cost effective and investigate which DSM strategies could be implemented with the highest return under certain conditions. A further investigation includes the demonstration of the advantages of DSM to the various stakeholders.

The successful implementation of DSM could have various advantages for the whole of South Africa, ranging from economical to environmental advantages.

The next chapter focus is on a more detailed study of DSM.



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2 Demand side management

2.1 Introduction

In the previous chapter it was determined that DSM is an option to resolve many issues Eskom is currently facing. To understand the full impact of DSM, this section gives a brief overview on DSM. The section investigates the following topics:

- Background on DSM ⇒ A survey was done on the history, the definition, and the various groups in which DSM can be divided in.
- Implementation of DSM in the commercial sector ⇒ A short description of how DSM can be applied in the commercial sector, illustrating the potential savings.
- A survey of actual DSM applications ⇒ A short survey is given of some of the DSM projects that have been undertaken in South-Africa in recent years.

2.2 Background on DSM

During the 1890's at the Thomas A Edison Pearl street generation facility in New York City, the only nighttime load was that of the lighting. This situation prompted Edison to initiate a campaign aimed at filling the daytime valleys. The result of this was increased loads due to electric motors. By the early 1930's the situation has turned a full circle, with utilities having increased capacity, thus searching for new nighttime uses of electricity. (Holmes, 1991:1)

DSM involves a deliberate intervention by the utility in the market place to change the configuration or magnitude of the load shape (Gellings & Chamberlin, 1993:2). DSM activities are designed to influence electricity demand for the mutual benefit of the utility and the customer (Gellings & Chamberlin, 1993:4).

The term 'Demand-Side Management' (DSM) was first used in the United States in the early 1980's to describe the planning and implementation of utility activities designed to influence the time, pattern and/or amount of electricity demand in ways that would increase customer satisfaction, and co-incidentally produce desired changes in the utility's load-shape (Eskom, 2001).



DSM is an alternative to system expansion as well as a tangible means of providing customers with a valuable service. DSM was later adopted in the United Kingdom, Europe, and Australia. Today, DSM-associated initiatives are practised worldwide, although these initiatives are not necessarily referred to as DSM programmes. (Eskom, 2001)

In South Africa, DSM is still a relatively new concept to most. While Eskom formally recognised DSM in 1992 when Integrated Electricity Planning (IEP) was first introduced, the first DSM plan was only produced in 1994. In this plan, the role of DSM was established and a wide range of identified DSM opportunities and alternatives were available to Eskom. (Eskom, 2001)

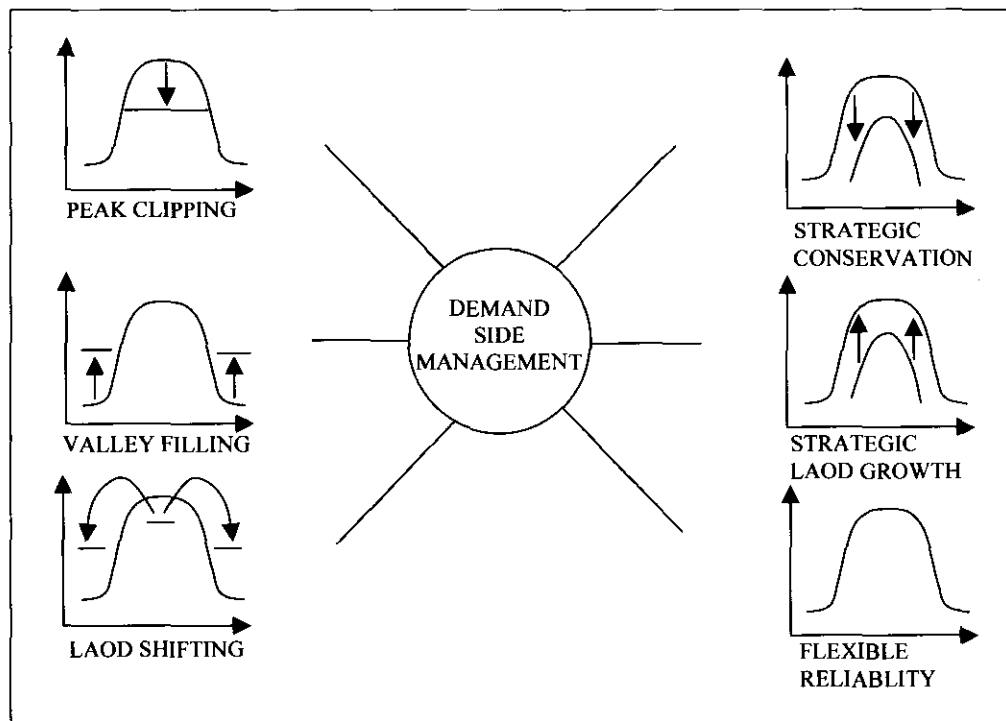


Figure 2-1: Load shaping objectives.

DSM procedures and strategies can be divided into various categories. These are:

➤ **Load shedding (peak clipping)**

Load shedding is the reduction of the demand, without effecting off peak demand (Lane, 1991:19). This is achieved by supervisory control of customer's appliances

as illustrated in Figure 2-1. The result of this is savings in peak-time electricity, thus money.

➤ Valley filling

Valley filling is the increase of off-peak demand without affecting peak demand (Lane, 1991:19) as illustrated in Figure 2-1. This is achieved by putting unused capacity to work (Morrison, 1991:38). The result is a lower average electricity bill for all customers.

➤ Load shifting

Load shifting shifts the demand from peak hours to off peak hours (Lane, 1991:19) as illustrated in Figure 2-1. This is achieved through the use of Thermal Storage Devices (TSD) (cooling or space heating) (Morrison, 1991:38).

TSD involves the heating or cooling of the infrastructure of a building at night, by the storage of ice or heating of ceramic bricks (Levine *et al.*, 1994. 44) and using the stored electricity in peak hours.

The results is, that the electricity consumption is moved from the peak hours with a high utility rate to off peak hours with a lower utility rate, thereby saving money.

➤ Strategic conservation

Strategic conservation involves the reduction of both peak and off-peak demand (Lane, 1991:19) as illustrated in Figure 2-1. This is achieved by encouraging customer selection of higher electricity efficient products, thereby lowering the total electricity demand. This will lead to electricity savings (money) over the whole electricity use profile.

➤ Strategic load growth

Strategic load growth involves the increase of both peak and off peak demand (Lane, 1991:19) as illustrated in Figure 2-1. This is achieved by increasing the demand during selected seasons or times of day. The result of this is that fixed capacity costs are over a larger base of electricity sales (Morrison, 1991:36) resulting in lower average electricity price for all customers.

➤ Flexible load shaping

Flexible load shaping involves tailoring service quality to individual customer needs (Lane, 1991:19) as illustrated in figure 2-1. This is achieved by adjusting the load, according to operating needs, thereby gaining more flexibility in supply planning (Morron, 1991:36). Customers with flexible load shapes could be presented with different incentives, to reduce their electricity use during peak times (Morron, 1991:36).

➤ Conclusion

From the previous paragraphs, it can be concluded, that through different DSM techniques electricity, and especially money could be saved. The total savings that are possible depends on the combination of the DSM techniques used. In the next section attention will be given into how DSM procedures and strategies could be implemented in the commercial sector and the potential savings that could be achieved.

2.3 Implementation of DSM in the commercial sector

2.3.1 Introduction

This section reports on a survey that was conducted to illustrate how DSM could be implemented in the commercial sector. Some of the techniques that are discussed could also be applied in the industrial or residential sector.

The DSM strategies and procedures under investigation are divided into the main applications they are used for. The categories investigated include:

- Heating, ventilation and air-conditioning systems;
- Lights; and
- Motors.

The focus of the survey was to:

- Indicate the electricity use share that the segment has;
- Various techniques how DSM could be implemented;
- The potential savings that could be obtained; and



- Problems that might be experienced with implanting the measures.

The focus of this section was not to give an in-depth discussion of the various measures, but rather to give an overview to illustrate the potential impact.

2.3.2 Heating ventilation and air-conditioning (HVAC)

According to Turner (1997) the mechanical heating or cooling of a building is dependent upon the various heat gains and losses experienced by the building. The primary purpose of a HVAC system is to regulate the indoor dry-bulb air temperature, humidity and air quality by removing or adding heat energy. HVAC accounts for a very significant portion of the energy of a building.

This section outlines the different DSM techniques that could be implemented in HVAC systems to save energy. These include:

- Energy efficient products;
- Central control systems;
- Thermal storage devices;
- Insulation;
- Low and no cost options for the HVAC system.

A Energy efficient products

Energy efficiency involves the use of more efficient products that lower the total energy consumption. Levine *et al.* (1994) reported that large air-conditioning systems of greater than 50 tons using rotary or centrifugal compressors, have a higher efficiency than reciprocal compressors.

Furthermore, Levine *et al.* (1994) reported that the most efficient products available in the U.S. market place have an efficiency of between 10 – 50 % higher than that of standard equipment.

The technologies used to increase the efficiencies include larger or improved heat exchangers, higher evaporative coil temperatures, more efficient motors and improved compressors.

B Energy Management and Control Systems (ECMS)

Energy Management and Control Systems (ECMS) involves the automatic regulation of the operation of the HVAC systems in a building. Levine *et al.* (1994) reported that the estimated savings of using ECMS are between 10 – 20 %. These savings could be achieved by the use of timers, occupancy sensors, daylight switches and so on.

ECMS can minimise unnecessary equipment operation and provide other functions such as economiser cycling or varying the supply air/water temperature depending on climatic conditions. ECMS are also used to limit peak electric loads by selectively switching off or cycling loads.

C Thermal storage devices

Thermal Storage Devices (TSD) involves the storage of ice or heat in a medium such as ceramic bricks, during the off-peak hours, for use in building during peak hours. Thus the electricity use is shifted from peak hours when the cooling or heating is needed to the off-peak hours.

With the use of “full storage” devices the peak electricity demand is typically reduced between 80-90% while with “partial storage” devices the reduction is typically between 40 –50% (Levine *et al.*, 1994:43).

D Thermal insulation

According to Turner (1997) thermal insulation plays a key role in the overall energy management picture. In fact, the use of thermal insulation is mandatory for the efficient operation of any hot or cold system. Most insulation systems reduce the unwanted heat transfer, either loss or gain, by at least 90 % as compared to bare surfaces.

E Economizers

One main advantage of all HVAC system is that they can utilize outside air to condition interior spaces when it is at an appropriate temperature and humidity.

The economizer cycle is most appropriate for thermally massive buildings which have high internal mass. Economizers cycles are ineffective in thermally light buildings and building loads that are dominated through the envelope of the building. (Turner, 1997:261)

The savings that could be achieved with economizers depends on the duration the system runs at off peak conditions (Turner, 1997:262).

F Conclusion

The implementation of a combination of HVAC systems could have a large impact on the total electricity use of a building. Levine *et al.* (1994) reported that HVAC conservation measures could reduce electric energy over 50 % for the HVAC segment of the bill.

2.3.3 Lighting

Lighting accounts for approximately 50 % of the electricity use of the commercial sector (Levine *et al.*, 1994:44) with estimated savings as high as 69 %.

DMS options for lamps are divided into four groups, these are:

- Lamps ⇒ Lamps can generally be divided into three light types. These include incandescent, florescent and high intensity discharge lamps.
- Starting gear ⇒ In general all lights, with the exception of incandescent systems, also require a ballast to control the voltage supplied to the lamps.
- Luminaries ⇒ Lamps have luminaries to project, or reflect the light source to the area needed.
- Lighting controls ⇒ Light controls offer the ability for light system to be turned on and off either manually or automatically.

The focus of the next few paragraphs is on how each component works (or what their function is), techniques to improve the efficiency and problems that might exist or that need to be remembered.

A Lamps

A.1 Incandescent

Incandescent lamps represent the oldest electricity lighting technology (Turner, 1997:348). The lamps emit light by passing an electric current through a tungsten wire to make it glow. With this method of generating light only about 5% of the electricity consumed is converted into light, the rest is lost as heat (Osram, 2001).

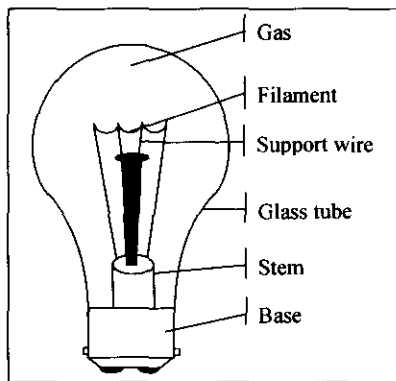


Figure 2-1: Schematic layout of a incandescent lamp

Higher efficiency in incandescent lamps could be achieved by filling the in closed capsule with halogen gas. As a result the filament burns hotter and more efficient, reducing electricity cost up to 15 % compared to general service lamps (Levine *et al.*, 1994:44).

Generally higher efficiency is achieved by the use of Compact Fluorescent Lights (CFL). CFL is a relatively new development that uses only about 10 - 20 % off the electricity of incandescent lamps, but still has the same light intensity.

Because CFL's do not have a point source like incandescent, they are not as effective in projecting light over a distance. The light is more diffused and difficult to focus on intended targets in directional applications. CFL's also don't last as

long, when rapidly switched on and off, and lumen output decreases with time (Turner, 1997:349).

Despite these difficulties, most CFL provide light comparable to incandescent lights, while significantly reducing electricity consumption. Even if light output are slightly reduced, the benefits of CFL's are large enough so that they usually remain cost-effective investments. (Turner, 1997:349)

A.2 Fluorescent lamps

Fluorescent lamps generate 70 % of all artificial light in the world. The success of these lamps can be attributed to their extremely long life of about 12 000 hours (an ordinary incandescent light bulb lasts just 1000 hours) and to their impressive economy (Osram, 2001).

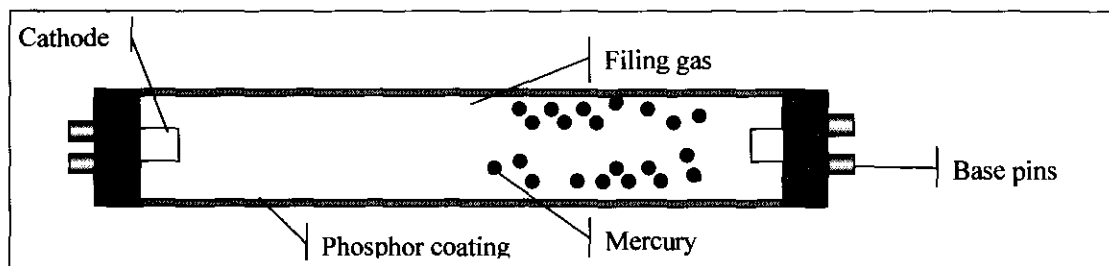


Figure 2-2: Schematic drawing of a Fluorescent lamp

Fluorescent lamps are low-pressure gas discharge lamps in which the invisible UV radiation generated by the discharge is converted into visible radiation thus light with the aid of phosphors.

Electricity savings in fluorescent lamps is mainly achieved through more efficient lamps. In the mid 1970's the first generation of electricity saving fluorescent lamps, substituted Krypton for Argon as the inert gas in the lamps. The lamps efficacy (lumens of light per watt of power input) was increased by about 3%. (Levine *et al.*, 1994:45).

The second generation of improved fluorescent lamps, was introduced in the early 1980's. The lamps contained improved phosphors, that resulted in a

5 - 15% increase in efficacy, along with a good colour rendering (Levine *et al.*, 1994:45).

Finally electricity savings were achieved with smaller diameter fluorescent lamps (26 mm vs. 38 mm). The smaller diameter reduces energy losses without a change in the light output.

For example 4 ft 38 mm (T12) tubes consume 40 W of energy while 26 mm (T 8) tubes consume only 36 W of energy, with no change in the lighting output (Levine *et al.*, 1994:45). This may sound very insignificant but in a commercial building lighting account for up to 50 % of the electricity expenditure and thus a 10 % saving could make a significant difference.

A.3 High-intensity discharge lamps

High-Intensity Discharge (HID) lamps produce light by discharging an electric arc through a tube filled with gasses. These lamps are point source lamps, which means refractors and light pipes can be effectively used to direct the light (Turner, 1997:349).

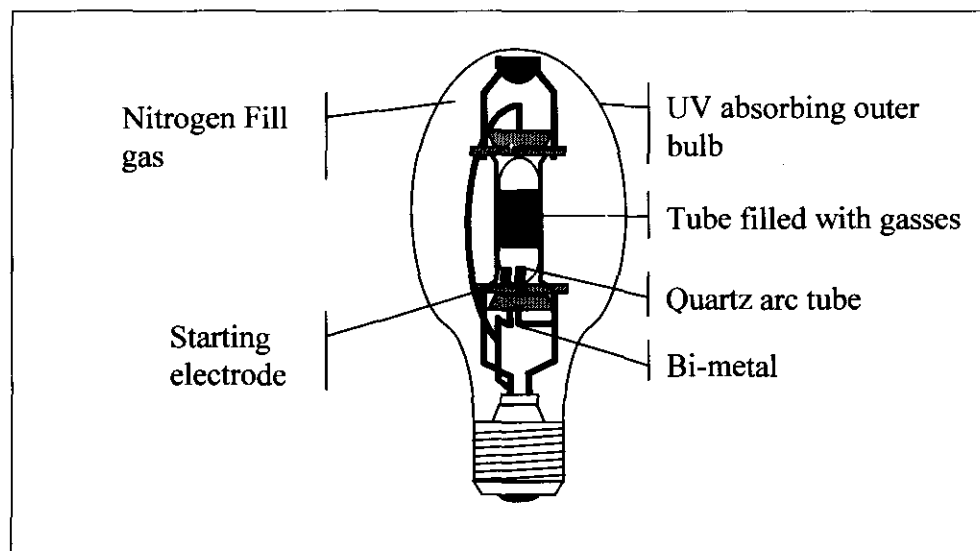


Figure 2-3: Schematic layout of a high intensity discharge lamp

Levine *et al.* (1994) reported commercially HID lamps can be derived into 5 types namely, mercury vapour, metal halide, high-pressure sodium and low-pressure sodium. These are named in order of their efficacy, from high to low.

There are significant opportunities in upgrading from less efficient to more efficient lamps types. The most common upgrade is from mercury vapour to high-pressure sodium.

In the selection of the lamp, it is important to determine whether the colour rendering is of great importance. For example when high colour rendering is important, metal halide lamps could be used, whilst where colour rendering is unimportant, low-pressure sodium lamps could be used.

B Starting gear

Nearly all lighting system excluding incandescent lamps require a ballast to operate (Turner, 1997:351). All discharge lamps cannot directly operate on the main voltage because of their negative internal resistance (Osram, 2001). A ballast is needed to provide a suitable starting voltage thereby limiting the current supplied to the lamps (Turner, 1997:351).

Ballasts are generally divided into two groups, namely conventional and electronic control gear.

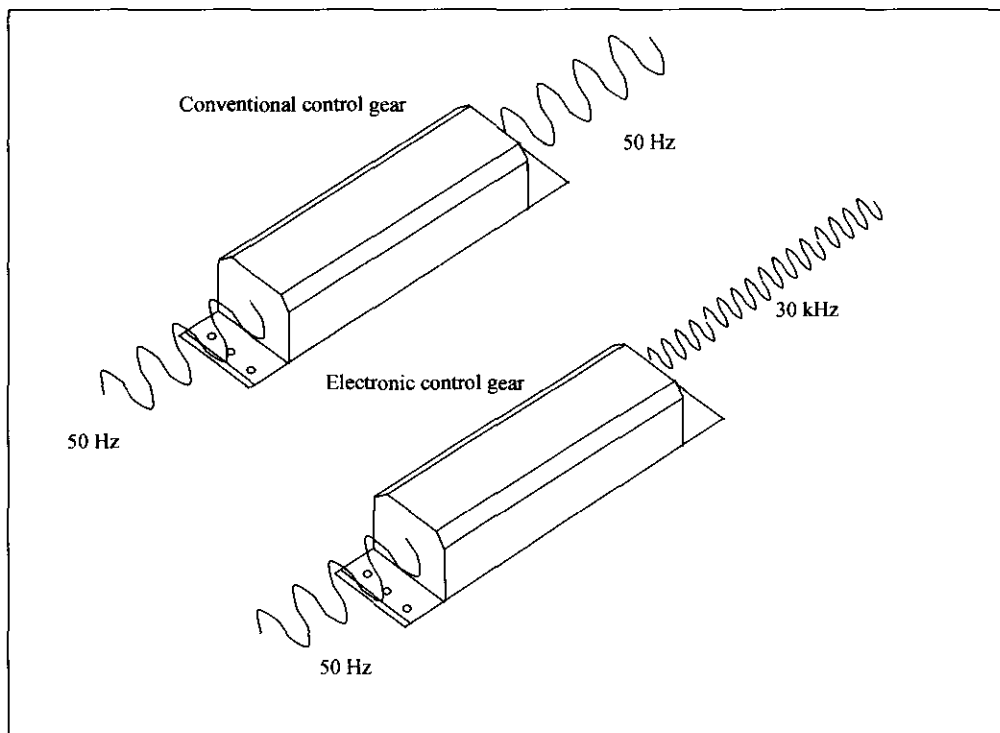


Figure 2-4: Conventional and electronic control gear

Conventional control gear (CCG) is a simple inductive resistor comprising an iron core around which copper is wound. Because of the ohmic resistance, there are considerable power losses and thermal output. Currently a high percentage of fluorescent lamps still use conventional control gear. (Osram, 2001).

CCG dissipate about 20 % of the total electricity power entering a fixture. In some developing countries poor quality ballast may dissipate as much as 30 % of the energy entering the fixture.

More efficient electromagnetic ballasts were introduced in the mid 1970's. The ballast makes use of better materials including copper winding and high-grade steel. This reduced the ballast losses, between 50 % and 60 %. By disconnecting the cathode after the arc is struck, another 5 % could be saved (Levine *et al.*, 1994:44).

Electronic control gear (ECG) operate at frequencies of 30 kHz or above (Osram, 2001). Lamps operating at these frequencies produce about the same amount of light, while consuming up to 30 % less power than CCG ballast. Other

advantages of ECC include less audible noise, less weight, virtually no lamp flicker, dimming capabilities (Turner, 1997:351) and a 50% longer lamp life compared to CCG (Osram, 2001).

C Luminaries

Luminaries are used to project or reflect the light source to the required area. With the use of better luminaries and by decreasing the height of the light electricity savings could be achieved.

An optical reflector could be used to increase the amount of light emitted from a fixture. The use of an optical reflector typically increases light output by 75-100%, thereby permitting the reduction of the number of fixtures (Levine *et al.*, 1994:44).

By decreasing the height of the lamps by half, 75 % less light have to be used for the same lumen output (SIEMP, 1997:7-2).

D Lighting design and control

Lighting design and control involves matching the used lighting to the required lighting, which in turns saves amount of electricity required. This is achieved by through various techniques.

Multilevel switches allow lights levels to be adjusted manually so that the lighting matches the need. Timers automatically turn off lights during periods when a building is unoccupied. (Levine *et al.*, 1994:45) Savings of up to 15 % could be achieved with these systems.

Occupancy sensors use infrared or ultrasonic sensors to turn lights on or off. It is estimated that for large office areas, savings of up to 15% could be achieved. (Levine *et al.*, 1994:45).

Daylight controls automatically reduce lamp output when daylight is sufficient to maintain or supplement required illumination levels. The systems combine a photocell sensor with a dimmable lighting system. The system is applicable to perimeter zones of buildings as well as interior zones where skylights are installed. Savings of up to 50% could be achieved in areas within approximately 5 meters of windows and skylights (Levine *et al.*, 1994: 45).

2.3.4 Motors

Motors are the largest end-user of electricity in most countries of the world with approximately 20 % electric energy usage in the commercial sector (Levine *et al.*, 1994:45). Motors convert electrical energy into mechanical energy that is produced as a result of attraction and repulsion between magnetic poles in the rotor and stator that produce a torque. (McPherson, 1981:13).

DSM opportunities for electric motors could be applied by the use of higher efficient motors, variable speed drives, and transmission devices, as well as no-and low cost options.

A Higher efficient motors.

The efficiency of motors could be increased through improved motor design and the use of more and better materials.

The use of larger diameter conductors, in the stator and rotor windings, could decrease the motor losses. Through the reduction of the thickness of the core laminations, Eddy current loss could also be decreased. Finally using high quality bearings reduces the friction of the motor. (SIEMP, 1997:9-25)

The energy use of higher efficient motors in the U.S. is typically 2 to 15% less than standard motors with an increased initial cost of between 10 to 30%. The operating cost of a single motor in a year often exceeds that of the purchase price, and thus even small gains in efficiency quickly pay for the initial capital outlay (Levine *et al.*, 1994:45).

B Variable speed drives (VSD)

In many motor applications, there is need for the power to vary over a time period. For example, in commercial buildings cooling and heating ventilation systems need often to supply more air on hot summer days than on mild days. To vary the speed of the motor VSD are used. VSD vary the frequency that the motor receives, thereby changing the speed of the motor. The potential saving with the use of VSD devices could be between 40 to 50% (Levine *et al.*, 1994:45).

C Transmission devices

The efficiency with which transmission devices transmit energy varies considerably. For example a "V-belt" has an efficiency of 90 to 96%, "Synchronous" and "flat" belts have an efficiency of 96 to 99 %, worm gears between 55 and 94 % and the slightly more expensive "helical and bevel gears" between 90 and 98 %. Savings could be achieved through the use of more efficient transmission devices (Levine *et al.*, 1994:46).

D Low cost and no cost options

A good maintenance plan on electric motors could reduce the motor's electricity use, saving between 10 to 15%. Optimal sizing of motors and pumps could also reduce losses depending on the size of the current- and new motor (Levine *et al.*, 1994:45).

In many facilities motors are run independently of the system installed. By simply switching off motors that are not used, significant electricity cost savings may be achieved. Another way to improve the efficiency of motors is to improve the power quality. Levine *et al.* (1994) reported that savings between 1 and 15% could be achieved by correcting the problem.

2.3.5 Conclusion

In this section an investigation was launched to determine what DSM is. It was found that the objective of DSM is the deliberate intervention of the utility provider to change the configuration of load profile by smoothing out the peaks and valleys. This is done so that the load profile closely resembles that of the utility. DSM is generally implemented through six strategies, namely: Load shedding; valley filling; load shifting; strategic conservation and flexible load shaping.

In the commercial sector DSM strategies could be implemented through in three segments namely: HVAC system; lights and motors. For HVAC systems DSM could be implemented through the use of more efficient product, energy control system and thermal storage devices. The savings that could be obtained depend on the combination of the DSM measures proposed. Savings of up to 50% have been reported.

In most countries fluorescent lamps account for the largest part of the artificial lighting in the commercial sector. For fluorescent lamps, DSM strategies could be implemented through the introduction of higher efficient electronic control gear and thinner fluorescent tubes. Savings up to 30% could be achieved.

Forslee (2001) reported that the Table View area experienced an unprotected load growth during 1991 to 1997, as illustrated in Figure 2-6. As a result, substantial network upgrades were needed in 1999.

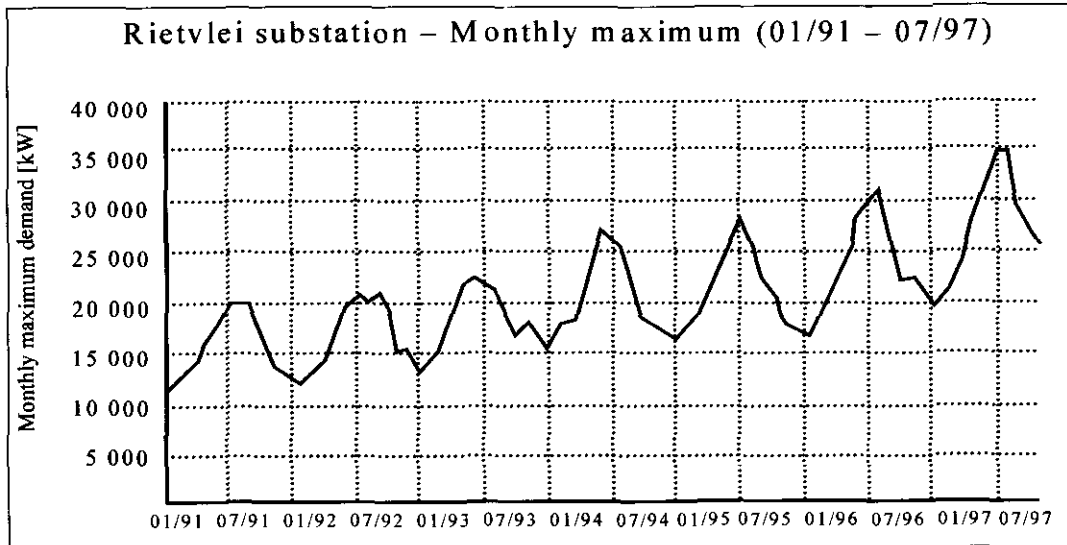


Figure 2-6: Table View monthly maximum demand growth

Eskom decided to launch a DSM project that would reduce the peak demand. The plan envisioned a load management system that was aimed at controlling the geysers load of the Table View area during peak periods. This load management system had to ensure that customers never or seldom experience a lack of hot water. It was hoped that with the implementation of a load management system in the Table View area, it would defer the network upgrades planned by a few years.

To manage the system, it was decided to install 10 000 load switches. This translated into a potential controllable load of at least 10MW during the winter period with the assumption that at the morning winter peak, we are able to obtain 1kW per geyser controlled.

The implementation of the project commenced during the latter half of 1998 and continued through to 1999. Upon completion of the project, 9850 load switches were installed in the Table View area.

A load test that was performed on the 19 August 1999 is illustrated in Figure 2-6.

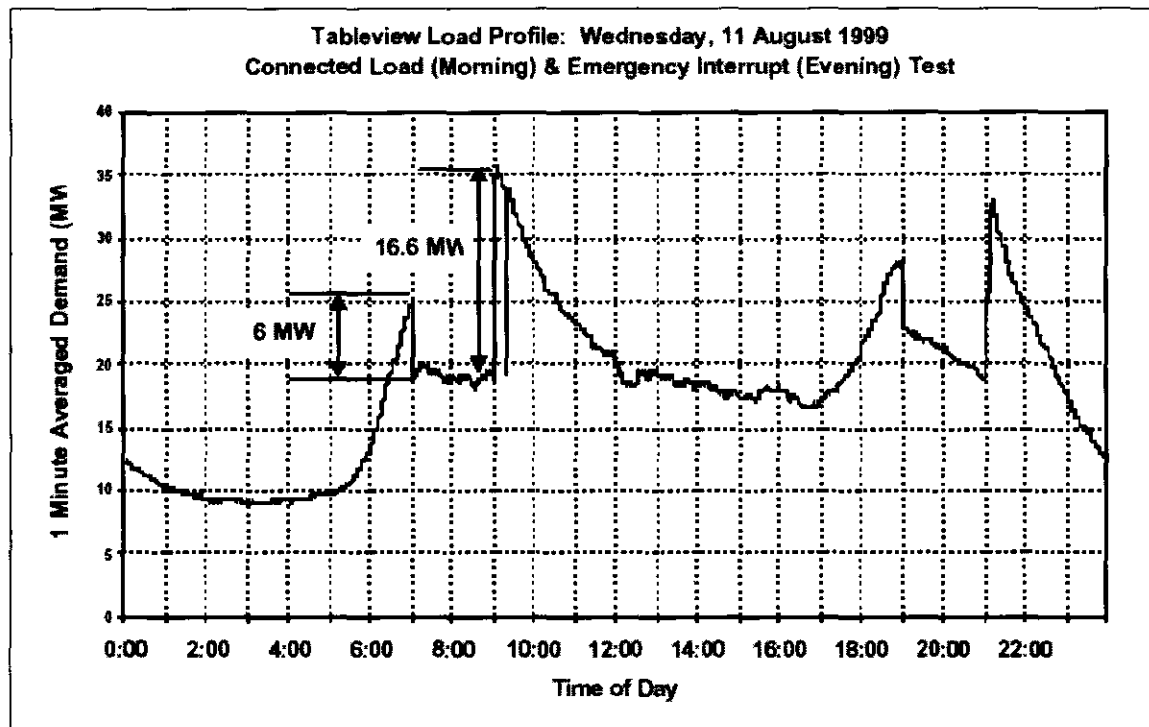


Figure 2-7: Load profile for Table View area on the 11 August 1999

The graph indicates that when the geysers were switched off at 7am, the diversified geyser load presented in the load profile was 6 MW. After keeping all the geysers off during the peak period, 16.6 MW of water heating load which represents the connected geyser load on the Table View system. This connected load represents 8500 installed geyser load switches at that date.

2.4.3 Hartebeespoort Dam energy efficient lighting initiative

Hartebeespoort Dam lies only 35 kilometres west of Pretoria in the beautiful Magaliesberg mountain range. The dam was completed in 1923 and has become a very popular holiday and weekend resort for Johannesburg and Pretoria. The area includes the towns of Schoemansville and Kosmos.



Figure 2-8: Aerial view of the Hartebeespoort area.

Holm (2001) reported in 1998 Eskom entered a formal agreement with the International Finance Corporation under a project development fund grant to produce a business plan for a South African energy efficient initiative. The initiatives aim, was to enhance the market penetration of energy efficient lights and fittings where Hartebeespoort was one of the areas.

In this project CFL lights were advertised in various newspapers as an alternative for the conventional incandescent lamps. The residents of the area could then buy the CFL at the local Hartebeespoort Municipal offices, in Schoemansville, when they paid their accounts. The lamps were sold at a price of R 50 for two, with the remainder sponsored by Eskom.

In total approximately 3000 CFL were sold in over 2000 homes in the Hartebeespoort area as part of the project. The result was that another 17 homes could be fed off the existing 400-kVA system in the Hartebeespoort area.

The estimated saving for the municipality was R 37 500 per annum. Finally, with every CFL installed, the end-user gains an estimated R 174 over the life span of the lamp.

2.4.4 Megawatt Park

Megawatt Park, Eskom head office, is located in the suburb of Sandton, Johannesburg. It is a single tenant building with small shops located on the ground floor and a total occupation of approximately 4420 people. The building has four storeys and a total floor area of 107 407 m² of which is 102 167 m² lettable office space.

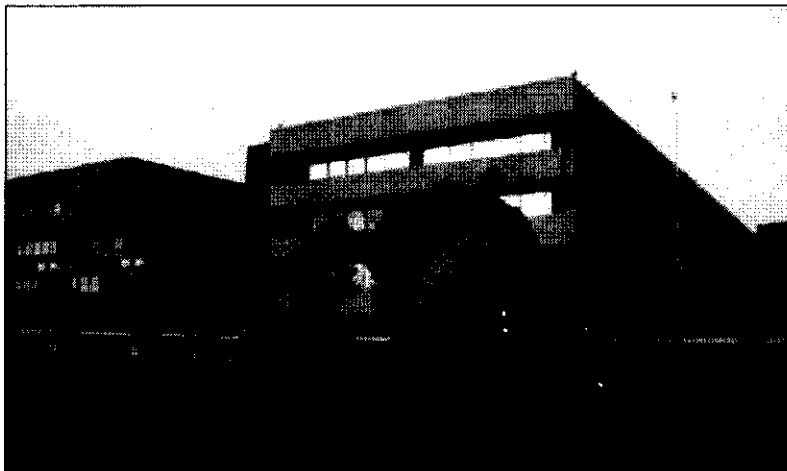


Figure 2-9: Megawatt Park

The building is occupied on weekdays from 08:00 to 17:00, and is usually not occupied on weekends except for cleaning staff.

As the country's primary electricity supplier, Eskom launched a DSM project to demonstrate the potential what DSM could have.

Over the past 10 years a complete revamp of the entire Megawatt complex was done from an energy management perspective. An audit was conducted and it was observed that the two primary sources of wasted electricity were the old style fittings and the air-conditioning units.

Some 60 000 light fittings were changed to provide more efficient illumination. Another aspect involved the incorporation of a building automation system, ensuring that if any employee should work late only, one twenty fourth of the lighting in an office floor (which can be up to 150 meters long) is switched on.

Variable speed drives and switching equipment were also employed to control the HVAC plants, for of peak conditions. This resulted in reduced runtime, reduced electrical consumption and a longer lifespan for the equipment.

During 1999 Megawatt Park saved approximately two million Rand in contrast to what it would have paid if no energy savings were introduced. This represent an annual cost savings of 28 %.

2.5 Conclusion

In this chapter an investigation was launched to determine what DSM is. It was found that DSM objective is the deliberate intervention of utility provider to change the configuration of load profile by smoothing out the peaks and valleys. This is done that the load profile closely resembles that of utility. DSM is generally implemented through six strategies namely: Load shedding; valley filling; load shifting; strategic conservation and flexible load shaping.

DSM is mainly achieved by the use of higher efficient products, central controlling systems and thermal storage devices, the maintenance of the equipment, resizing of equipment and switching off unnecessary loads. The total effect of these techniques depend on what stage the building is in and how much the building owner is prepared to spend.

Finally three examples were given for various cases where DSM was implemented. The findings suggest that DSM has the potential to modify the energy use profile. Savings of up to two million Rand were reported.

The next chapter investigates various techniques in the establishment of a baseline. His baseline is then used to determine the hourly long-term impact of DSM in a region.

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Establishment of a baseline for various purposes

3.1 Introduction

In the previous chapter it was illustrated how DSM could be used as a viable alternative for the various problems Eskom and South Africa faces. To determine the impact if DSM in an area, an accurate baseline has to be established. This chapter focus is in the current techniques used in industry to establish a baseline.

This chapter discusses the following two categories:

- Baseline $\Rightarrow$ A brief introduction is given into what a baseline is.
- Establishment of a baseline $\Rightarrow$ Various techniques concerning the establishment of a baseline are discussed here. This section is subdivided into the following subsections:
 - Calibrate simulation approach and
 - Inverse approach

The survey was evaluated by means of the following guidelines:

- What is the basis of this technique.
- How can the technique be used for the establishment of a baseline.
- What are the most important advantages using this technique.
- What are the most important disadvantages using this technique.
- What conclusions can be drawn from the work?

The aim of these sections is not to give a detail account of how these techniques work, but rather to determine the advantages as well as the possible shortcoming of using the techniques for application of a region.

3.2 Baseline

A baseline is the energy profile of a utility or utilities if DSM strategies and procedures were not implemented. The problem is that the actual impact of DSM cannot be measured directly. This is because the baseline indicates how the utility electricity profile would be, if no changes were done, as illustrated in Figure 3-1. A baseline has to be inferred from mathematical or computer simulations.

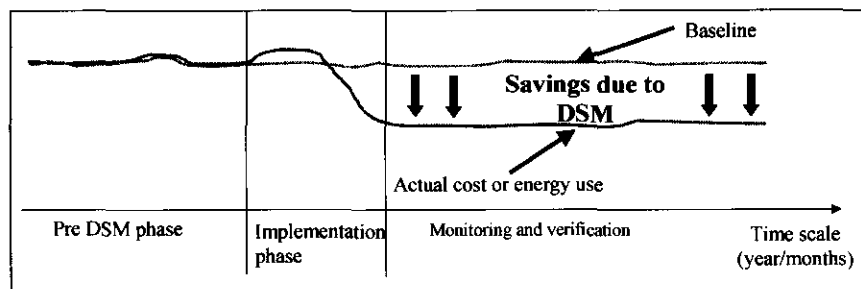


Figure 3-1: Impact of DSM

In general DSM activities promote various energy savings. These changes are units of electricity that are no longer used. Thus they are no longer there and one cannot measure something that does not exist. The problem with the baseline is that it can never be absolutely known. (Waltz, 2000:158). It has to be inferred or established from mathematical or computer simulations.

To shed some light on the subject, it can be explained by asking what the effect of a rise in the petrol price is on the price consumer's pay for merchandise. At first glance it seems simple, it is the price increase due to the petrol price increase, the difference between what it was previously, and what it is now. The problem is that there are other factors that also have to be brought into consideration, such as inflation and demand and supply. Thus a model has to be developed that can simulate the effect of these different factors.

The following paragraphs aim is to shed some light on the various techniques that can be used to model or establish the baseline.

3.3 Establishment of the baseline

Haberl *et al.* (1998) reported in the simplest cases the baseline could be modelled by directly using the measured electricity use. Unfortunately this simple comparison can contain as much as a 10 to 20 % error in buildings that have varying schedules and or experience different weather condition after the implementation of DSM. Thus it is not a viable option.

Alternatively the baseline can be inferred or modelled. The basic approaches used to model the baseline can be divided into two generic types (Haberl *et al.*, 1998:842).

- Calibrated simulation approach.
- Inverse models

The following paragraphs will give a short description of the different approaches.

3.3.1 Calibrated simulation approach

With the calibrated simulation approach one uses an existing building's simulation program and “tunes” or calibrate the different physical inputs to the program so that the simulated electricity use closely matches the actual electricity use.

Vien *et al.* (1994) reported simulation software that incorporates engineering models is commonly used in the calibrated simulation approach. Engineering calculations have always been an integral part of the estimation of the electricity savings. This is mainly due to their simplicity, their flexibility, their relative low cost, and their inherent ability to be understood and used by users.

In the engineering models all energy related appliances, processes, or systems (Physical models) could be depicted in a mass-balance relationship (Gellings *et al.*, 1996, 9-44). This technique begins with a physical description of the building system or component of interest. For example, the building geometry, geographical location physical characteristics, type of equipment, type of heating and cooling system and operating schedules are used to predict the peak and average electricity use of such a building (ASHREA, 2001). An illustration of this concept is given in Figure 3-2.



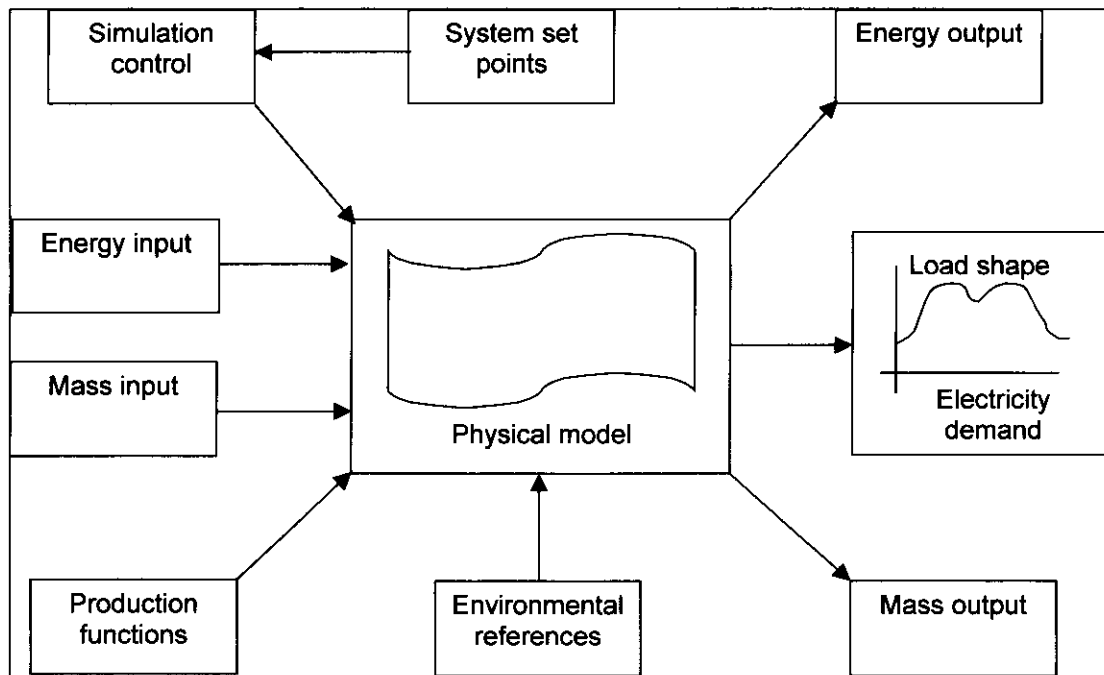


Figure 3-2: *Engineering simulation model*

Schuldt (1999) reported the calibration process typically consists of three steps. First, the building characteristics data, derived profiles, and aggregated electricity measurements are integrated into the simulation. Secondly, the simulation is run to calibrate predicted end-use consumption under measured site weather conditions. The predicted end-use result of the whole building is then compared to the corresponding electricity use. In the final step, adjustments are made to the simulations inputs until the simulated electricity use match that of the actual electricity use.

Several iterations of the simulation are usually required to achieve a comparison between the simulated and the actual electricity use that satisfies all calibration criteria. For each simulation changes are made to the elements that have the highest uncertainty. In commercial building these typically include heating and cooling temperatures, HVAC control parameters etc.

ASHRAE reported (2001) the main reservations for the widespread use of calibrated simulation are that they are labour-intensive, requires a high level of user skill and knowledge in both simulation and practical building operations, they are time consuming and are often dependent on the person doing the calibration

Truly “calibrated” models have been achieved only in a few applications. This is because they require a large amount of input parameters, a high degree of expertise, and enormous amounts of computing times, patience and financial support.

The main reservation of this approach for use in a region is that all the individual buildings have to be simulated separately until the electricity use is calibrated. For a large area, the problems experienced escalate, and it is thus not a viable option to model the electricity use of the region on an hourly basis.

3.3.2 Inverse models

ASHRAE (2001) reported that in the case where the input and output variables are known and measured an inverse model is used.

The objective of an inverse model is to determine a mathematical description of the system and to estimate the parameters. In this case actual performance data has to be available for the model development and identification.

In general, an inverse model use model parameters that are deduced from actual building performances. These parameters are much more likely to capture the system performance taking into account the actual development of the building. Performance data collection and model formulation need to be appropriately tailored for the specific circumstances. This often requires a higher level of skill and expertise of the user.

Inverse models can be classified according to ASHREA (2001) into two broad categories. These are:

- Grey box approach and
- Empirical or black box approach,

The following paragraphs will give a short description of the different approaches.

A Grey box approach

With the grey box approach, a physical model is first formulated to represent the structure or physical configuration of the building, and then important parameters representative of certain key and aggregated physical parameters and characteristics are identified by a statical analysis.

This approach requires a high level of expertise both in setting up appropriate model equations and in the estimation of these parameters. Often an intrusive experimental protocol is necessary for proper parameter simulation. This technique has great potential for fault detection and diagnosis and on-line control, but its applicability to whole building electricity use is limited (ASHRAE, 2001:31.25).

B Empirical or “Black box” approach

AHREA (2001) reported with the empirical approach a simple or multi-variant regression model is identified between the measured electricity use and the various influential parameters (climatic variables, building occupancy).

The form of the regression model can either be purely statistical or loosely based on some basic engineering formulation of the electricity use in the building. The identified model coefficients are such that none or very little meaning can be assigned to them. This approach can be used for any timescale, provided that the appropriate data is available.

Model identification is straightforward and requires little effort. These formula can be used in several diverse types of circumstances. The empirical approach is the most widely used inverse approach.

C Division of the empirical and grey box approaches

ASHREA (2001) reported in general the empirical and grey box approaches can be divided into two categories:

- Steady state models and
- Dynamic state models.

Steady state models are those that do not consider the effects such as thermal mass or capacitance that causes short-term temperature transient. Generally these models are appropriate for monthly, weekly and daily data and are often used for baseline development

Dynamic models capture effects such as building warm-up or cool down periods and peak loads. A simple criterion in determining whether a model is a dynamic model or not, is to investigate if a time-lagged variable exist.

C.1 Steady state model

Generally steady state models are used to capture the electricity use of a building as a function of the driving force that has an impact on the building electricity use. There are two types of steady state models that can be used for modelling building electricity use. These are:

- Single variant
- Multi variant

C.1.1 Single variant

The simplest steady state inverse model is one developed by regressing monthly utility consumption data against average billing period temperatures. ASHRAE (2001) reported that Ruch and Clardige suggested a four parameter model, which is based on the mean monthly temperature to model the electricity use of a building. Thus these models use a single variable to model the electricity use of the utility.

The advantages of these steady-state inverse models are that their use can easily be automated and applied to a large numbers of buildings where monthly billing data and average daily temperatures are available. ASHREA (2001) also reported that Kissock *et al.* applied steady state single variant inverse models with success using daily data.

The disadvantages of steady state single variant models include:

- Insensitivity to dynamic effects e.g. thermal mass
- Insensitivity to variables other than temperature e.g. humidity and thermal gain.
- They are inappropriate for buildings with strong schedule dependent loads.

Commercial buildings, in general have a high internal heat generation, which makes the electricity use of a commercial building less strongly influenced by outdoor air temperature.

ASHRAE (2001) reported that single variant models had mixed success at modelling the electricity use in commercial buildings. ASHRAE (2001) also reported that the single linear regressions could be used to model the electricity use for a daily and monthly time scale.

Eskom need is to determine the hourly impact of the DSM measures that are investigated. No literature was found that could support an hourly baseline using single variable models.

C.1.2 Multivariable models

ASREA (2001) reported multivariable models are logical extensions to single variable models. The aim in using multivariable models in modelling the electricity use of a utility is to characterize the utility electricity use with a few readily available and reliable input variables.

Multivariable models require more metering and are unusable if one of the variables becomes unavailable. In addition, some of the repressor variables may be linearly correlated. This can results in large uncertainty in the estimation of the

regression coefficients and also lead to poorer model prediction accuracy compared to a model where the repressors are not linearly correlated. (

ASHRAE (2001) reported that Reddy & Katipamula *et al.* successfully used multivariable techniques to model single building electricity use and HVAC systems. These models correlate the electricity use of the system under investigation with that of the dry bulb temperature, the lighting load, solar load and latent effects via the outdoor temperature.

ASHREA (2001) reported that multivariable models have been found to be very accurate for daily time scales and slightly less accurate for hourly time scales. This is because changes in the way the building is operated during the day and the night lead to different relative effects of the various repressors on the electricity use.

The mentioned effect cannot be accurately modelled by one single model. ASHRAE (2001) reported that Katipamula *et al.* found that by breaking up the electricity use data into hourly bins corresponding to each hour of the day and then identifying 24 individual hourly models leads to appreciably greater accuracy.

No information was found that indicated this technique was previously tested for the hourly simulation of the electricity use of a region. Thus, a technique has to be developed and tested using linear regression for the case of a region using region hourly base.

An alternative option is to use already developed models to simulate the electricity use of specified single buildings. In this technique the buildings are simulated separately. Thus, the single building's hourly electricity has to be known, and this is rarely the case. Furthermore, if all the information is available, this approach is labour-intensive, requires a high level of user skills and is very time intensive.

C.2 Dynamic models

Dynamic inverse models are usually used for the modelling of hourly or sub-hourly data, in cases where the thermal mass of a building is sufficiently significant to delay heat gains or losses. Dynamic models traditionally require a set of differential equations.

ASHRAE (2001) reported that Rabl, Braun and Anderson *et al.* used dynamic inverse models for commercial building electricity use simulation.

ASHRAE (2001) reported that the disadvantages of inverse dynamic models include their complexity and need for more detailed measurements to tune the model. Dynamic models also require a high degree of user interaction and knowledge of the building system.

No information was found that indicated this technique was previously tested for the hourly simulation of the electricity use of a region. Thus a technique has to be developed and tested using linear regression for the case of hourly simulation of the electricity use of region.

An alternative option is to use already developed models to simulate the individual electricity use of the different buildings. In this technique the buildings are simulated separately. Thus the single building hourly electricity use has to be known, and this is rarely the case. Furthermore, if all the information is available, this approach is labour-intensive, requires a high level of user skills and is very time intensive.

3.3.3 Conclusion

In this chapter an overview was given on what a baseline is. The different techniques used to baseline the electricity use of a building were also presented.

A baseline can be described as what the electricity profile of a utility would have been if no DSM changes were made. The baseline cannot be measured, it can only be inferred from mathematically or computer simulations. There are two broad

techniques used to infer or simulate the electricity profile. These are, the calibrated simulation approach and inverse models.

For the calibrated inverse approach one uses an existing building simulation program and tunes or calibrates the various physical inputs of the program so that the simulated electricity use matches that of the actual electricity use. The main reservation with this technique is that it is labour intensive, requires a high level of user skill and knowledge.

Furthermore, this technique is only used on single building simulations and cannot be used to simulate the total regional electricity use. For a region, all the individual buildings have to be simulated and the problems experienced with single buildings simulations therefore escalate.

The objective of an inverse model is to determine a mathematical description of the system and to estimate the parameters from actual building performance.

No information was found that indicate that inverse techniques were previously used to model the hourly electricity use of a region as a whole. This approach still has to be tested. The main reservation with using this approach for regional use, is that inverse models usually are labour and cost intensive, are time consuming and require a high user skill and knowledge.

An alternative is to simulate the electricity use of the individual buildings in the region. Thus individual models that simulate the electricity use of the individual buildings have to be developed using the different techniques.

The main reservation with the use of this approach in a region is that all the individual buildings have to be simulated separately until the electricity use is calibrated. For a large area, the problems experienced with single simulation escalate, and this technique is therefore not a viable option to model the electricity use of the region.

Neural networks (NN) can be considered as an alternative to model the baseline electricity use of a region. Neural networks are considered to be intuitive because

they “learn” from example rather than following program rules. This ability of NN to “learn” is one of the key aspects of NN. The following section investigates NN.

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4 Neural Networks

4.1 Introduction

In the previous chapter different techniques were discussed that could be used to establish a baseline. Neural Networks (NN's) could be considered as a good alternative in the establishment of the baseline. The aim of this chapter is to give an overview of NN's.

This chapter is divided into the following sections:

- Background on NN ⇒ a description is given of where NN's originated, and on the basic components of NN's.
- Basics on NN ⇒ A description is given on the basic concepts that are used in NN.
- NN Structures ⇒ A wide variety of NN's exist. An overview is given of the most popular NN's that are used.
- The relationship between statistical methods and NN ⇒ There is considerable overlap between the fields of neural networks and statistics. The similarities are discussed, and reasons are given why NN are chosen above statistical methods.
- A literature survey of the use of NN was undertaken to establish if NN's were previously used to baseline or forecast the electricity use of a region. ⇒ The literature survey aim was to investigate previous attempts to model the electricity use of a region or to forecast the electricity use of a region.

4.2 Background on NN

Neural networks (NN's) have the capability to learn complex non-linear dependencies without prior knowledge of the intrinsic relations (Warren, 1997). This property makes NN ideal to establish a base year model as the electricity use of substations, with their buildings, are intrinsically linked to a number of factors such as occupancy, usage, temperature, relative humidity, time of day, month, etc.

In practice a NN is especially useful for classification of problems which have large amounts of training data available, but to which hard and fast rules cannot easily be applied (Warren, 1997).

NN's are inspired by neuroscience. The brain consists of millions of cells, connected through synapses. These synapses are used to store information, while the cell is the central body of the neuron that controls all the logical and biological functions of the neurons (Olofsson *et al.*, 1998:106).

All natural neurons have four basic components, which are dendrites, somas, axon, and synapses. Basically, a biological neuron receives inputs from other sources, combines them in some way, performs a generally non-linear operation on the combination, and then gives the final result. The figure below shows a simplified biological neuron and the relationship of its four components.

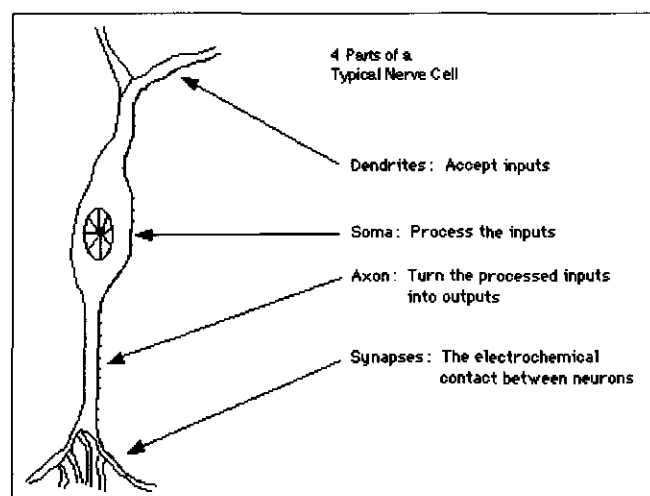


Figure 4-1: Human brain dendrite

NN's do not mirror the complexity of the human brain. There are however many similarities. Firstly, the building blocks of both networks are simple computational devices that are highly interconnected. Secondly, the connections between the neurons determine the function of the network. (Hogan, 1996:1-9)

Currently, there are a large number of different NN structure and techniques available. Because of the enormous extent of the field, only the basic concepts of the networks structure and some of the terminology used are described briefly as background to this dissertation.

4.3 Basics Components of NN

Although much of the development of neural networks has been inspired by biological neural mechanisms, the link between artificial neural networks and the biological neural systems are rather tenuous.

Biological organisms are simply understood efficiently to allow any meaningful emulation. As a result, NN's are better interpreted as a class of mathematical algorithms (Aldrich, 2000:16).

NN's are composed of basic units or artificial neurons that are analogous to the neuron in the human brain. In general terms NN consists a large number of primitive process units also known as nodes that are connected on a massive parallel scale. It is only through the collective behaviour of these nodes, the NN can realise their powerful ability to form generalized representations of complex relationships and data structures (Aldrich, 2000:16).

A typical understanding of the structure and functioning of a typical neural network node is therefore necessary for a better understanding of the capabilities of NN's. The basic concept of an artificial neuron is presented in more detail in the following paragraphs.



4.3.1 Models of single neurons

Each node consists of a processing element with a set of input connections, as well as a single output connection as illustrated in Figure 4-2

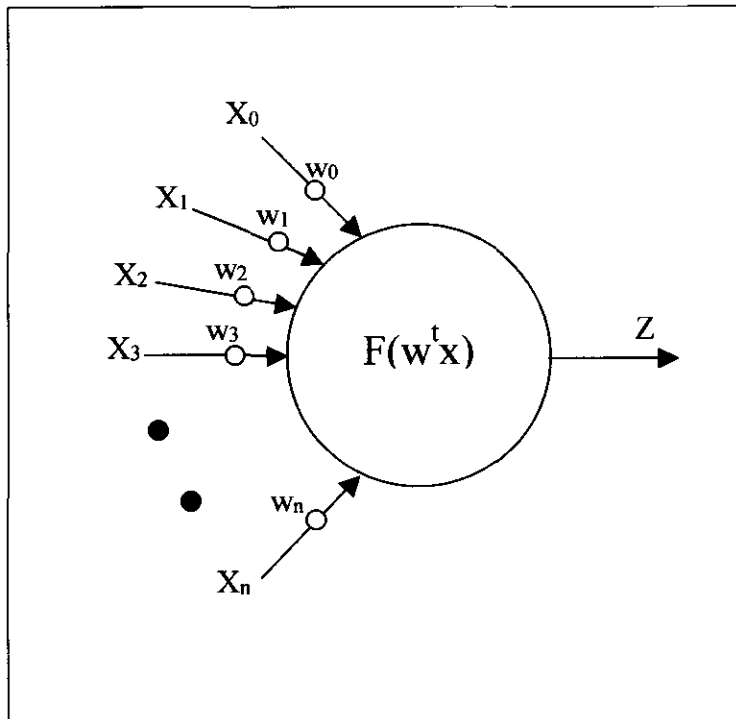


Figure 4-2: Model of a single neuron

Each node receives input data (x_i), processes it, and delivers a single output. (Medsker *et al.*, 1994:168). Each input connection in the processing element is associated with a quantity called a weight or a connection strength (w_i). The weight represent the relative strength of the different connections, in other words the relative importance of the specific input (Medsker *et al.*, 1994:168).

For a specific unit, all the inputs (x_i) are multiplied by its weights (w_i) and these are then summed. The summed result is then fed through an activation function or transfer function (f_i) that transforms the weighted sum into the final value (y_i). The argument of the activation function is sometimes referred to as the potential of the node.

This process can be described as:

$$y_i = f_i \left(\sum_{j=1}^n [w_{ij} \cdot x_j] \right), \text{ or} \quad [2.1]$$

$$= f(w^T x)$$

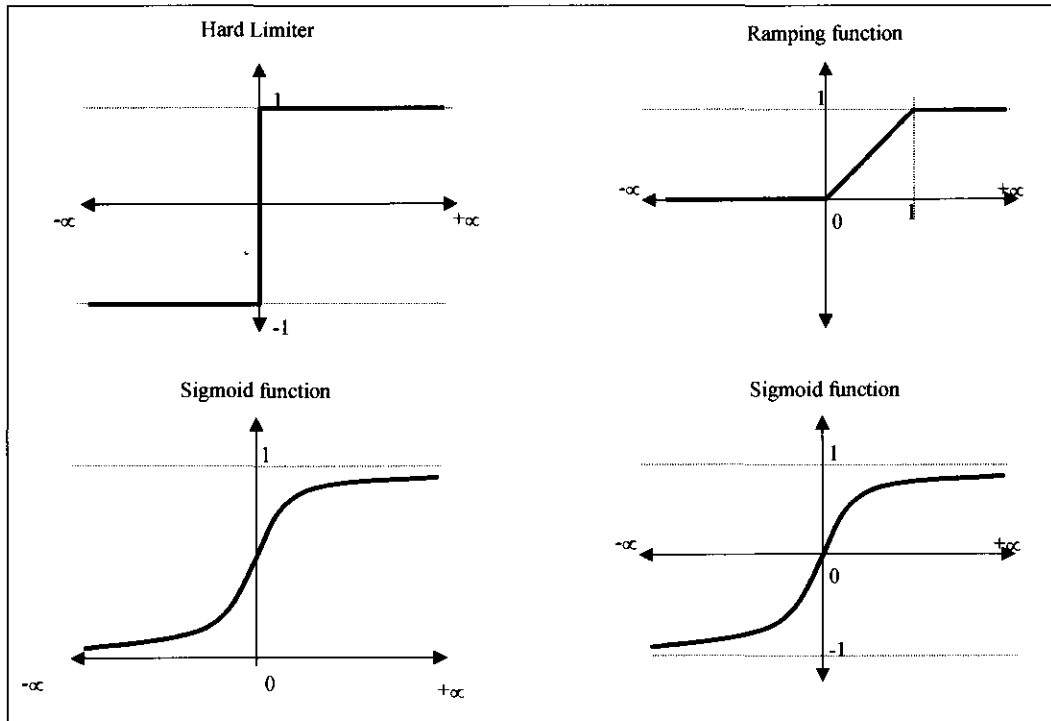


Figure 4-3: Sampler transfer functions

Transfer functions are generally non-linear. Transfer functions are categorised into four types, these include:

➤ Hard limiter or step transfer function

This transfer functions output depends upon whether the result of the summation is positive or negative. The hard limiter sets the value of the neuron to 0 if the argument value is less than zero, or 1 if the value its argument is larger than one (Hogan *et al.*, 1996:2-4). This type of function is illustrated in Figure 4-3

➤ Linear transfer function

This transfer functions output is equal to its input (Hogan *et al.*, 1996:2-4).

➤ Ramping function

The transfer function's output could be a mirror of the input within a given range, for example zero to one, but could function as a hard limiter outside that range. It can be described as a linear function that has been clipped to minimum and maximum values as illustrated in Figure 4-3 (Nelson & Illingworth, 1991:47).

➤ Sigmoid or S-shaped curve

This transfer function takes the input that may have a value between plus and minus infinity and squashes the output into a smaller range. For the output range of 0 to 1, the Sigmoid (0,1) function is used which is described in equation [2.2]

$$f = \frac{1}{1 + \exp(-w^T x)} \quad [2.2]$$

This is graphically illustrated in Figure 4-3

For the output range of -1 to 1, the Sigmoid(-1,1) function is used that is described in equation [2.3] (This is graphically illustrated in Figure 4-3)

$$f = \frac{1 - \exp(-w^T x)}{1 + \exp(-w^T x)} \quad [2.3]$$

NN's consists of many interconnected neurons or nodes. The next paragraph gives a short description of how single neurons are connected to form a multiplayer perceptron.

The output's signal from a node may be passed on as input to other processing elements, or even possibly sent back as an input to itself. In general there are two ways of connecting the elements:

- *Feedforward* ⇒ No processing element output can be an input on the same layer or a preceding layer. Feedforward NN's usually produce a quick response to an input. Most of the feed forward NN's available can be trained using a wide variety of efficient conventional numerical methods, with the addition of algorithms invented by NN researchers (Sarle, 1997).
- *Feedback* ⇒ Outputs can be directed back as inputs to previous or same level nodes. For some cases these epochs¹ take a long time before a response is given as each time an input is presented, the NN must iterate for a potentially long period of time. In general it can be said that feedback NN's are more difficult to train than feed forward NN's (Sarle, 1997).

Finally NN's use some sort of training rule that changes the various variables in NN. The aim of the training rule is to minimize the error. This concept is discussed in the next paragraph.

4.3.3 Learning functions

Learning can be described as the modification of behaviour, following upon and induced by interaction with the environment (Nelson & Illingworth, 1994:128).

In NN's the transfer function remains fixed for the life of the processing element. The transfer function is generally seen as part of the design of the NN. The objective of learning or training is to find a set of weights that will correctly interpreted all the sets of input values (Medsker *et al.*, 1994:168).

Learning typically occurs by means of algorithms designed to minimise the mean square error between the desired and the actual output of the NN through the incremental modifications of the weight matrix of the NN (Aldrich, 2000:19).

¹ An epoch is a complete pass through the pattern or records of a training set

In general there are two main kinds of learning algorithms or learning modes, these are (Sarle: 1997):

- In **supervised learning**, the correct results, also known as the target values or desired outputs, are known and are given to the NN during the training process. This is done that the NN can adjust its weights in order to match its outputs to the target values. After training, the NN is tested by giving it only input values, not target values, thereby to verify how close the NN model comes to the desired output target values. For the verification process, the NN must preferable use unknown the data, in order to assess the performance on unknown data.
- In **unsupervised learning**, the NN is not provided with the correct results during the training process. Unsupervised NN's usually perform some kind of data compression, such as dimensionality reduction or clustering.

The distinction between supervised and unsupervised methods is not always clear-cut. Supervised methods come in two sub varieties: auto-associative and hetero-associative.

In auto-associative learning, the target values are the same as the inputs, whereas in hetero-associative learning, the targets are usually different from the inputs.

On the other hand an unsupervised method can learn a summary of a probability distribution and can then use that summarized distribution to make predictions. Many unsupervised methods are equivalent to auto-associative supervised methods found in the supervised method (Sarle, 1997).

Many learning rules are in common use. Most of these rules are variations of the best-known and oldest learning rule, namely Hebb's rule (Nelson & Illingworth, 1994:137). The following paragraphs will give a short description of the working of these rules. There are many more training techniques than these mentioned and every week more are being invented. The most common rules are listed below. (Nelson & Illingworth, 1994:137)

A Hebb's rule

Donald Hebb introduced the first rule. The rule basically states that if a processing element receives an input from another processing element, and if both are highly active the weight between the processing elements should be strengthened.

B Delta rule

The delta rule is based on the simple idea of continuously modifying the strengths of the connections to reduce the difference (delta) between the desired output value and the current output value of a processing element. This rule is also referred to, as the least mean square learning rule, as it minimizes the mean square error.

C Gradient descent rule

The gradient descent rule uses a mathematical approach to minimize the error between actual and desired outputs. The weights are modified by an amount proportional to the first derivative of the error with respect to the weight. The rule is often used, even though it converges very slowly to a point of stability.

D Kohonen's learning rule

Teuvo Kohonen developed this rule. It was inspired by learning in biological systems. It is employed only in unsupervised learning network applications.

In this procedure the processing elements compete for the opportunity of learning. The processing element with the largest output is declared the winner. It is permitted an output, and only the winner plus its neighbours are permitted to adjust their weights.

E Back Propagation learning

The back propagation of errors technique is the most commonly used generalization of the delta rule. The procedure involves two phases.

The first phase, called the forward phase, occurs when the input is presented and propagated forward through the network to compute an output value for each processing element. For each single neuron, the output is compared with desired output, and the error is computed.



In the second phase, called the backward phase, the recurring difference computation is now performed in a backward direction. Only when these two phases are complete, new inputs can be presented.

Generally this technique is applied to hierarchical networks of three or more layers. At the output layer, there's no problem, as the output from each node is known. The trick comes in adjusting the weights on the hidden layer, as it is unknown what each individual neuron from the preceding layer contributes towards the total error. This information is received from the forward phase. Thus with two phases all the weights can be appropriately adjusted.

4.3.4 Conclusion

NN's are considered to be intuitive because they learn by example rather than by following programmed rules. The ability to learn is one of the key aspects of NN's.

A NN consists of input layers, one, or more hidden layers, and an output layer. Each layer is made of processing elements or neurons. Each neuron receives information from various sources and then assigns a weight to it. The weighted inputs are then summed and fed through an activation function.

The NN trains by adjusting the different weights associated with the various inputs of all the neurons. The objective of the training procedure is to change the weights that the simulated output closely resembles that of the desired output.

The following section illustrates the various similarities that exist between NN techniques and statistical methods. Some of the direct similarities are discussed and finally the advantages of using NN's over statistical methods are given.

4.4 The advantages of NN over statistical methods

This section illustrates the main similarities as well as the differences between the various NN techniques and Statistical methods. Secondly the main reasons why NN's are chosen above Statistical techniques are given.



A The relationship between statistical methods and NN's

There is considerable overlap between the fields of neural networks and statistics. This section describes the overlap based on the research done by Sarle (1997)

Statistics is concerned with data analysis. In NN terminology, statistical inference means learning to generalize from noisy data. Some neural networks are not concerned with data analysis (e.g., those intended to model biological systems) and therefore have little to do with statistics. Then there are some NN's do not learn and therefore have little to do with statistics. While some neural networks can learn successfully only from noise-free data they would therefore not be considered as statistical methods.

Most NN's that can learn to generalize effectively from noisy data are similar or identical to statistical methods. These are for example:

- Feedforward nets with no hidden layer (including functional-link neural nets and higher-order neural nets) are basically generalized linear models.
- Feedforward nets with one hidden layer are closely related to projection pursuit regression.
- Probabilistic NN's are identical to kernel discriminant analysis.
- Hebb's learning is closely related to principal component analysis.

Then, finally, there are some NN areas that appear to have no close relatives in the existing statistical literature, these are:

- Reinforcement learning.
- Stopped training (the purpose and effect of stopped training is similar to shrinkage estimation, but the method is quite different).

Feedforward nets are a subset of the class of non-linear regression and discrimination models. Statisticians have studied the properties of this general class but had not considered the specific case of feedforward NN's before such networks were popularised in the neural network field.

Still, many results from the statistical theory of nonlinearly models apply directly to feedforward nets, and the methods that are commonly used for fitting non-linear models, such as various Levenberg-Marquardt and conjugate gradient algorithms,



can be used to train feedforward nets. Among the many statistical concepts important to NN's is the bias/variance trade-off in nonparametric estimation.

While NN's are often defined in terms of their algorithms or implementations, statistical methods are usually defined in terms of their results. The arithmetic mean, for example, can be computed by a (very simple) backpropagation net, by applying the usual formula $\text{SUM}(x_i)/n$, (where x_i is the i data point investigated and n is the number of data points) or by various other methods.

What one gets is still an arithmetic mean regardless of how one compute it. So, a statistician would consider standard backpropagation, Quickprop, and Levenberg-Marquardt as different algorithms for implementing the same statistical model such as a feedforward net. On the other hand, different training criteria, such as least squares are viewed by statisticians as fundamentally different estimation methods with different statistical properties.

It is sometimes claimed that NN's, unlike statistical models, require no distributional assumptions. In fact, NN's involve exactly the same sort of distributional assumptions as statistical models, but statisticians study the consequences and importance of these assumptions while many NN workers ignore them. For example, least-squares training methods are widely used by statisticians and NN's workers.

Statisticians realize that least-squares training involves implicit distributional assumptions in that least-squares estimates have certain optimal properties for noise that is normally distributed with equal variance for all training cases and that is independent between different cases. These optimal properties are consequences of the fact that least-squares estimation is maximum likelihood under those conditions.

Hundreds, perhaps thousands of people have run comparisons of neural nets with "traditional statistics". Most such studies involve one or two data sets, and are of little use to anyone else unless they happen to be analysing the same kind of data.



The question that arises is why rather use NN's rather than any of the statically methods? There are many answers to that question depending on what kind of NN's one is interested in. The focus of the next few paragraphs is to illustrate the main reasons why NN are preferred over Statistical Methods.

B Why use NN's

NN tends to be useful in the same situations as projection pursuit regression, i.e.:

- The number of inputs are fairly large;
- Many of the inputs are relevant; but
- Most of the predictive information lies in a low-dimensional subspace.

The main advantage of NN over projection pursuit regression is that computing predicted values from a NN is simpler and faster.

Also, NN's are better at learning moderate pathological functions than are many other methods with stronger smoothness assumptions, as long as the number of pathological features (such as discontinuities) in the function is not too large.

Thus, although NN have many similarities with statistical methods, the advantages make them more variable. The next section gives a short overview of the literature on how NN's were used in the industry.

4.5 Literature survey of the use of NN's in industry in order to baseline or forecast the electricity use of a region

In this section a short literature survey was conducted on the previous use of NN in the construction of a baseline. To the authors best knowledge no literature was found on the applications of NN's for the construction of a baseline. The majority of research done, focussed rather on the forecasting of the maximum demand for a specific region using different indices.

A summary is given of the cases where NN's are used in the construction of a baseline, as well as the long-term forecasting of the electricity use of a region.



The survey was evaluated by means of the following guidelines:

- What work has been done?
- How was the work done?
- What are the most important results that have been obtained?

4.5.1 Long-term load forecasting using improved recurrent neural networks

Yasuhiro Hayashi and Shinichi Iwamoto (1994:41) developed the technique at the Waseda University to forecast the maximum electricity demand. Hayashi and Iwamoto proposed the use of recurrent neural networks (RNN), as it has the ability of learning patterns from past records. This technique used the back propagation model, which is excellent at pattern recognition.

Hayashi and Iwamoto estimated the growth of the electricity use in Tokoy area by using the following as input parameters.

- Growth rate of the proceeding year;
- Growth rate of number of diffused air conditioners from proceeding year;
- Growth rate of the gross national product from the preceding year'; and
- Growth rate of the mining industry production index from the preceding year.

By using a sliding window, Hayashi and Iwamoto forecasted the maximum demand of the next few years, by correlating the mentioned parameters of the past few years with the current years maximum demand. The current data was then used to forecast the annual maximum demand for that region.

The advantage of this technique is that "it" can facilitate learning with very high speed compared to conventional learning techniques. It can be used very effectively to forecast the maximum demand for the next few years.

4.5.2 Artificial neural networks as applied to long-term demand forecasting

Tawfiq Al-saba and Ibrahim El-Amin (1999:189) at the King Fahd University of Petroleum and Minerals developed this technique to forecast the maximum electric demand.



Al-saba and Ibrahim proposed the use of back propagation as it has the same features that make the operation of a NN more reliable. These are that the training is designed to minimise the mean square error between the desired output and the actual training technique. It is also a supervised training technique, thus it enables the designer to generate the desired result.

Al-saba and Ibrahim estimated the growth of the electricity use in an area by using the previous data points, by the incorporating a time series. The NN model was applied yearly from 1981 to 1996. After the NN was trained, it was used to forecast peak demand form 1997 to 2006.

They then compared it with actual loads for 1997 and 1998. The best error of both NN cases is less then the utility error. From this it was possible to state that NN models can provide relative long-term forecasting with a minimum number of historical data points.

This technique can thus be used very effectively to forecast the electricity for a region. The results indicate that it has a higher accuracy than that was estimated by the utility.

4.5.3 Genetic programming model for long-term forecasting of electric demand

This technique was developed by Dong Gyu Lee, Byong Whi Lee and Soon Heung Chang (1997:17) at the Department of Nuclear Engineering in Korea, to forecast the maximum electric demand.

Lee *et al.* proposed the use of Genetic Programming (GP) for the long term forecasting of electric power demand. GP uses Genetic Algorithms (GA) to search through a space of possible computer programs for one which is nearly optimal in its ability to perform a particular task. It does not require an assumption of any functional relationship between the dependent and independent variables.

Since annual electricity power demand is mostly affected by population and Gross Domestic Product (GDP) these variables were used as independent variables to



forecast the long-term electricity power demand. The results represented by them indicate that the GP model performs better than the regression model for long-term forecasting of power demand.

The greatest advantage of this technique is that does not require assumptions of functional relationships between the dependent and independent variables. Thus it requires little to know user intervention.

4.5.4 Up to year 2020 load forecasting using neural nets

Bahman Kermanshahi (1998:125) at the department of Electronics and Information Engineering developed this technique to forecast the maximum electric demand for 9 utilities in Japan.

Kermanshahi proposed that for the use of NN's for the long-term load forecasting of an electric load.

The inputs for the networks were:

- Gross National Product (GNP);
- Gross Domestic Product (GDP);
- Population;
- Number of households;
- Number of air conditioners;
- Amount of CO₂ pollution;
- Oil price;
- Amount of energy consumption;
- Electric price; and
- The maximum demand for that specific year as the output.

Kermanshahi trained the NN on twenty years of available data. A sliding window was proposed for this research. The sliding block holds a 10 year block of data with which it then trains the NN on, and then forecast the loads for the next year.

This was done for every year from 1985. The actual data was used for forecasting the loads of 1975 - 1994. However, for forecasting loads beyond 1994, the



forecasted data was applied. There results indicated an error of 3 % for the verification year, and a 10 % error is acceptable for Japan.

From Kermanshahi work it can be conclude that the maximum demand for a specific year could be forecasted using a twenty-year sliding window. Kermanshahi extended the concept of Hayashi and Iwamoto by including more factors which seems to give more accurate results for a longer period of time.

4.5.5 Conclusion

The previous paragraphs gave some examples of practical applications in using NN's for the long-term forecasting of the electricity use of a region. To the author's knowledge no work was found, that indicated the use of NN to establish a hourly baseline for the electrity use of a region.

As a result, the survey was extended to include the long-term forecasting for a region. From the survey it is observed that the work conducted mainly focussed using economic and various other variables such as GDP, CO₂ emissions, number of electrified households to forecast the electricity use of a specific region. Generally a sliding window approach was used to forecast the electricity use. The results that were achieved, gave higher accuracy results than what the utility forecasted.

The drawback of all these options is that it uses yearly or monthly data for the forecasting. For Eskom it is of greatest importance to determine what the impact of a specific DSM programme has on the hourly electricity use. The mentioned techniques thus cannot be used effectively to determine the impact of DSM in a region.

4.6 Conclusion

In this chapter an overview was given on NN's and their basic components were discussed. NN's have the advantage that little knowledge is needed from the different inputs. The NN finds the relationships that exist between the inputs and



outputs. It has the further advantage that it can determine which inputs given have the greatest effect on the model.

NN models are inspired by the human brains own architecture. NN's consists of many simple processors or units. The different inputs are multiplied by a weight and summed in the unit. A transfer function then adjusts the value, depending on which of the transfer functions is used.

A number of rules are used to adjust the internal processing. The way the weights are adjusted, for example affects the learning of the system. The power of the NN, lies in the interconnections of these units. No single unit gives much of a clue to the overall picture, it is rather the overall pattern of the interconnections among the different units and layers which determines the properties of the specific NN.

Currently there are an array of NN architectures available, all having their strengths and weaknesses, depending on the specific application they are used for.

The applications commonly found in industry focuses on the use of a NN with a mixture of economic inputs to forecast the electricity use of a region. The major disadvantage of these techniques is that they use monthly or yearly data to do the calculations from. For the purpose of DSM it is preferable that data has to be in an hourly form to see the direct impact on the load profile. No application was found suggesting that a NN was used to construct the hourly electricity use of a region.

The next chapter describes how an hourly baseline is developed using NN's. The established baseline could then be used to illustrate the long-term hourly impact of the various DSM options.

4.7 References

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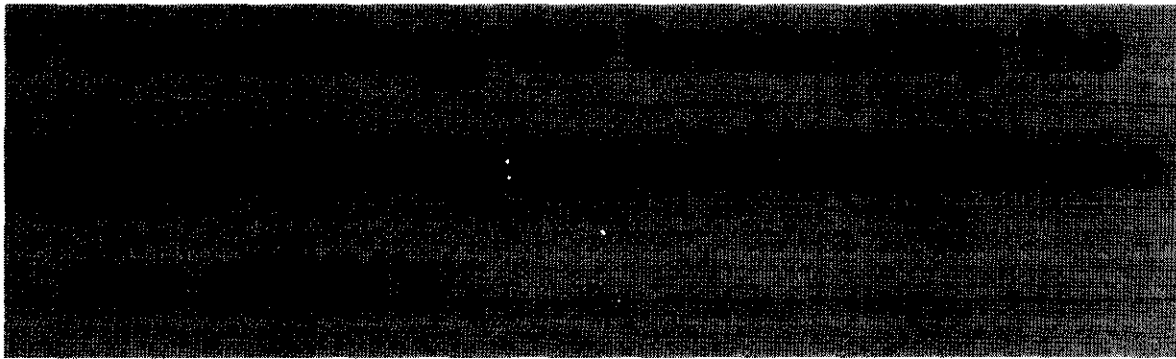
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5.1 Introduction

The previous chapter a brief overview was given into how NN work and could be applied in industry to forecast the electricity use in a region.

This chapter focuses is on how a NN can be applied in the construction of a baseline for the long-term forecasting of the impact of DSM in a region, using an hourly baseline model.

This chapter will be divided into sections for each of the main components in developing the model, these are:

- Limitations and boundaries
- Establishment of a baseline
- Model refinement
- Verification of the baseline
- Reduction of input parameters
- Normalizing the model
- Long-term forecasting of DSM in a region

5.2 Limitations and boundaries

Before the hourly baseline can be established, clear limitations and boundaries have to be set. For this dissertation an hourly baseline is constructed which is then used to forecast the long-term impact of DSM in a region. The following points are not included as part of this study:

- The estimation of market penetration of DSM,
- The estimation of the growth of electricity use for the region
- Economic and other factors that affect the estimates of future costs and savings

- Unpredictability in various economic issues, such as inflation, discount rate, electricity cost, and life of the system.

5.3 Establishment of a baseline

The first step in the calculation of the long-term effect of DSM on a region is to calculate the baseline. From this baseline all the calculations will then be made. The aim of this section is to determine the procedure for the establishment of an hourly baseline using NN's.

A full year's electricity data is likely to encompass the entire range of variations of both climatic and different operating modes of the buildings and the HVAC system. However, in many cases a full year's data is not available. One is thus constrained to develop models using less than a full year's of data. Consequently, it was first established if NN's could be used to establish a baseline, by using a full year of data. Once this has been established, a study was conducted to determine the minimum of data points necessary to successfully model the hourly baseline.

This sections deals with the procedure involved in the construction of a baseline using a full year's of data.

5.3.1 Construction of a baseline using Neural Networks

The first step in the construction of a baseline is to choose the different variables. The variables chosen have to be quantifiable factors and actual measurable factors (Willson,1998:881). The next two paragraphs will illustrate which variables are used for the construction of the baseline.

A.1 Input variables

The first step is to choose the main factors that influence the electricity use for a specific commercial area. Care has to be taken that all the underlying relationships are captured.



Only variables that have an influence on the electricity use should be included in the baseline. These exclude variables that are influenced by DSM activities. While weather variables are often the dominant cause of seasonal variations in electricity use of a region, other non-weather factors also affect the electricity use of a building. These non-weather factors include changes in operating hours, in base load and in occupancy levels. The variables included in this study are thus both weather and non-weather related variables.

The weather variables considered in this study include (ASHRAE 2001:31.27):

- Outdoor air temperature;
- Outdoor specific humidity;
- Solar radiation; and
- Wind speed.

The non-weather related variables considered include:

- Weekly schedules (Weak day and weekend);
- National holidays; and
- Regional Holidays, for example, at a campus students have holidays which influence the electricity use.

Some of these parameters vary little, although their effect on electricity use may be important, an inverse model will implicitly lump their effect into a parameter that represents a constant load. (ASHRAE, 2001:31.27)

Other independent variables may also be included in the study, depending on the availability of the data. For example, the occupancy of the specific area. This information could be obtained from access or security control systems if available.

A.2 Output variables

The output variable of the NN is the electricity use of that specific area on an hourly base. This hourly baseline is processed to obtain the monthly electricity use, maximum demand and electricity cost as well as the annual electricity use, cost and maximum demand.



B Modelling and refinement of the baseline

The second step in modelling the annual hourly baseline with NN's is to construct the baseline. In the construction of the baseline different factors influence the model output. This section gives a brief overview on different factors that have an influence on the results, and how they influenced the output of the trained model. Finally a refinement strategy is given that was used during this study.

B.1 Factors that influence the result of a NN

The factors that influence the output of a NN can be divided into two groups these are:

- Input variables and
- NN topology

B.1.1 Input variables

The use of the different input variables have a definite influence on the accuracy of the model. In choosing variables, the NN has to be kept as simple as possible. For example, if two points are available on psychometric chart, all the other variables are known. Thus for example only the dry bulb and humidity is needed. It is therefore unnecessary to indicate all the variables used.

Secondly, most of the datasets are quantitative variables but some datasets such as the day of the week, are categorical data and these have to be encoded to numerical values. Encoding changes data from a single data-point with any dimensionality to multi data-point with binary dimensionality. For example if the data set is as follows

1	Red
2	Green
3	Blue

Encoding changes this to

1	Red	1	0	0
2	Green	0	1	0
3	Blue	0	0	1

One needs to identify all these categorical variables, and change them to encoded data, as this assist the NN to better understand the relationships. The disadvantage is that with an increase in input variables the longer it takes to train the network.

B.1.2 NN topology

NN topology is concerned with the different ways in which the NN is made up. The following paragraphs explain the major factors that have influence the NN and how they affect the output.

➤ Transfer function

The transfer function may be a linear or non-linear function (Hogan *et al.*, 1996 1-8). There are a variety of transfer functions. The linear transfer functions are commonly used where there is a linear relationship between the input and output. Non-linear transfer functions for example the log-Sigmoid transfer function or Hyperbolic Sigmoid transfer, force the output into a predetermined range (Fahlman & Lebiere, 2001).

In general, linear models are useful in a wide variety of applications, and even for functions with a mild non-linearity, one can get better results with a simpler linear model than with a complicated non-linear model (Sarle, 2001).

➤ Number of hidden layers

The number of hidden layers depend in a sense on the architecture of the NN. For example, if one has only one input variable, there seems to be no advantage in using more than one hidden layer (Sarle, 2001). More than two hidden layers can be useful in certain architectures such, as cascade correlation (Fahlman & , Lebiere, 2001). Moreover, the number of hidden layers depend on which

technique is used and what data is modelled, with a higher number of hidden layer increasing the accuracy, but increasing the chances of over training (Aldrich, 2000:84).

➤ **Number of hidden neurons/units**

Selecting the number of hidden neurons/units is an art rather than a mathematical calculation. When the number of hidden neurons are small, the correlation of the output and input cannot be studied well, thereby increasing the error (Keramshi, 1998:125). There is no way to determine a good network topology just from the number of inputs and outputs. The number of training cases, the amount of noise, and the complexity of the function are all crucial elements (Sarle, 2001).

Generally a trial and error scheme is adopted to determine the appropriate number of hidden neurones, starting with a low number and increasing it till it fits. It has to be remembered that the higher the number of hidden neurons, the more complex the artificial intelligence network becomes and the longer it takes to train the network.

B.1.3 NN learning criteria

The NN learning criteria is concerned with the different ways the NN learns. The following paragraphs explain how the different learning criteria influence NN results.

➤ **Number of epochs**

An epoch is a complete pass through the pattern or records of a training set. For example if a backpropagation networks is trained for 500 epochs on a training se consisting of 100 records, it means that the networks has completed 500 000 forward-backward passes or iterations. In the above-mentioned example each record in the training set has therefore been presented 500 times to the network (Crusader systems, 1998:47)

➤ **Learning rate**

A smaller learning rate coefficient results in a slower convergence, but can locate smaller minima in the error surface than a larger learning rate coefficient. In essence, a smaller learning rate coefficient allows the algorithm to cover a larger proportion of the error surface, with a larger learning rate coefficient (Aldrich, 2000:84).

➤ **Momentum**

The use of a large momentum coefficient with a small learning rate increases the rate of convergence. Conversely, a small momentum rate requires a large learning rate to ensure stability (Aldrich, 2000:84).

B.2 Refinement strategy

Two strategies can be adopted in training a NN model, namely a top down model and a bottom-up strategy (Aldrich, 2000:84).

For a top down structure a large complex structure is initially specified and this structure is then gradually pruned down as indicated by the neural net to generalise the test data. (Aldrich, 2000:84)

The second strategy starts with as simple a model as the data would permit. The architecture is then incrementally made more complex until the NN model is able to generalise the test data sufficiently (Aldrich, 2000:84). In this study a mixture between these strategies was adopted.

For the input variables a top down structure is used to determine the sensitivity of the variable influence on the result. Not all of the variables are always available, thus the most influential variables have to be obtained.

For the NN topology, only the number of layers were adjusted. A down up strategy is used to keep the NN as simple as possible. Furthermore, the sigmoid (-1,1) function was used as transfer function throughout the study. As the

selection of the number of neurons is a skill rather a science, the number was kept as calculated by the program.

For the NN learning criteria, only the number of epochs was investigated. For this a down up approach is used to determine the effect on the accuracy, and keep the learning time as short as possible. From a preliminary investigation it was found that the learning rate and momentum have an insignificant effect on the result of the NN, thus they were left as is.

The aim behind the refinement strategy is to develop a model that is as simple as possible, and thereby can be used in the future with the greatest of ease.

5.4 Verification of the baseline

For modelling of a baseline it is crucial that the model is an accurate representation of the simulated data. The question arises as to when the model is accurate enough to be used for baseline purposes in the long-term forecasting of the impact of DSM, so that no further refinement is needed. Thus, the third step is to verify the accuracy of the model. If the model does not comply to set standards, further refinement has to be done. This is therefore an iterative process.

The verification of the models is based on the guidelines set by the California Energy Board for the verification of building models (CPUC, 2000:53-56). These models only apply to the verification of a single building, and not on a regional level. Furthermore, only the electricity use of the buildings is verified. Subsequently the guideline was adapted to suit the needs for the verification of buildings on a regional level.

The Large Non-residential Standard Performance Contract (LNSPC) program was started in 1998, when Pacific Gas and Electric -, the San Diego Gas & Electric - and Southern California Edison Company offered a new and innovative approach toward delivering energy-efficiency services to non-residential customers in their respective service territories. It was designed through the collaborative efforts of Energy Service Companies (ESCOs), environmental groups, customers, utilities,



and the newly created California Board for Energy Efficiency (CBEE), an advisory board of the California Public Utilities Commission (CPUC).

The following paragraphs discuss the verification guidelines as set out by the CPUC.

Firstly the data is evaluated in three categories:

- Electricity use;
- The monthly maximum demand; and
- Electricity cost basis.

Secondly, the baseline is verified using three indices, these include:

- Mean Bias Error (MBE) is the mean bias error between the simulated and measured data for the period investigated.
- Coefficient of Variation on the Root Mean Square Error (CV(RMSE)) is the root mean square error between the simulated and measured data for the period investigated.
- Error (ERR) is the percentage error between the simulated and measured data for the period investigated

These indices differ for each time period investigated. In the following section each of indices and their formulas, are given.

5.4.1 Calibration with hourly data, (whole building hourly data).

The hourly simulated data is compared to the measured data for each month investigated, using both the MBE_{month} and the $CV(RMSE_{month})$ indices.

MBE_{month} is calculated using the following formula:

$$MBE_{month} = \left(\frac{\sum_{month} (M - S)_{hr}}{\sum_{month} M_{hr}} \right) \times 100 \quad [5.1]$$

where M is the measured data and S is the simulated data for the same time instance. The MBE indicates how well the model predicts the output variable as



compared to the measured data. However, MBE is subject to cancellation error, where the combination of positive and negative values for $(M-S)_{\text{month}}$ serve to reduce MBE. To account for the cancellation $CV(RMSE)_{\text{month}}$ is also needed.

$CV(RMSE)_{\text{month}}$ is calculated using the following formula:

$$CV(RMSE)_{\text{month}} = \left(\frac{RMSE_{\text{month}}}{A_{\text{month}}} \right) \times 100 \quad [5.2]$$

where

$$A_{\text{month}} = \frac{\sum_{\text{month}} M_{hr}}{N_{\text{hours in month}}} \quad [5.3]$$

$$RMSE_{\text{month}} = \sqrt{\frac{\sum_{\text{month}} (M-S)_{hr}^2}{N_{hr \text{ in month}}}} \quad [5.4]$$

5.4.2 Calibration with monthly data (whole building with monthly data)

For monthly calibration, the monthly and annual data is compared using both the ERR and the $CV(RMSE)$ indices. Thus, the hourly data has to be added together for the same period for each month.

ERR_{month} is calculated for a specific month using the following formula:

$$ERR_{\text{month}} = \frac{(M-S)_{\text{month}}}{M_{\text{month}}} \times 100 \quad [5.5]$$

where:

$$M_{\text{month}} = \sum_{\text{hours}} M_{\text{hourly}} \quad [5.6]$$

and

$$S_{\text{month}} = \sum_{\text{hours}} S_{\text{hourly}} \quad [5.7]$$

ERR_{year} is calculated for the whole year investigated using the following formula:

$$ERR_{\text{year}} = \frac{\sum_{\text{month}} ERR_{\text{month}}}{N_{\text{month}}} \times 100 \quad [5.8]$$

Note that the monthly differences in measured and simulated electricity consumption may cancel each other, resulting in a smaller annual ERR. To ensure against cancellation of monthly error, the CV(RMSE) must also be verified.

$CV(RMSE)_{month}$ is calculated for every month using the following formula:

$$CV(RMSE)_{month} = \frac{RMSE_{month}}{A_{month}} \times 100 \quad [5.9]$$

Where:

The mean of measured data for the month

$$A_{month} = \frac{\sum_{year} M_{month}}{N_{month}} \quad [5.10]$$

and the root mean square error for the month is

$$RMSE_{month} = \sqrt{\frac{\sum_{month} (M - S)_{month}^2}{N_{month}}} \quad [5.11]$$

where N_{month} is the number of utility bills for the year.

The combination of ERR and CV(RMSE) can determine how well the model predicts the regions electricity use. The lower the ERR and CV(RMSE), the better the calibration.

5.4.3 Acceptable tolerance for data calibration

To determine if the data is indeed an accurate representation of the modelled data, a set of tolerances are set, that are based on the LNSPC program. To ensure that the NN model is actually a sound representation of the modelled data, the verification is performed using data the NN did not train on, commonly known also as test data.

Table 5-1: Acceptable tolerance for data calibration

Description	Time period	Comparison tool	Limit
Electricity use	Hourly data	MBE hourly	< 10%
		CV(RMSE)hourly	< 25%
	Monthly data	ERR monthly	< 15%
		ERR annual	< 10%
		CV(RMSE)month	< 15%
Max demand	Monthly data	ERR monthly	< 15%
		ERR annual	< 10%
		CV(RMSE)month	< 15%
Electricity cost	Monthly data	ERR monthly	< 15%
		ERR annual	< 10%
		CV(RMSE)month	< 15%

It is to be noticed that the MBE_{hourly} and ERR_{Monthly} is exactly the same value. The LNSPC indicates that only one of these have to be chosen to verify the building(s) electricity usage. For this study, both these indicators are given, with the smaller limit used as the indicator.

5.5 Minimizing of data points

Once it is established that the NN could be used to construct an hourly baseline, the data points needs to be minimized. This is mainly because a full year's data is not always available for the construction of the baseline.

Before a study can be conducted, it has to be pointed out, that gathering data is a sequential process. Thus it is pointless to do a study for example, where data is collected only every first week of the month and the rest is left out. The measuring time may be shortened, but the time to collect the data is still the same.

A better option is to select the data sequentially, but to reduce the measuring time from for example a full year of data to only 6 months of data. For this a full factorial study needs to be conducted on the different variables that influence the NN. A complete factorial study can be described as one in which several process

variables are identified as being of interest. The data is then collected under each possible combination of setting of the process variable. (Vardeman. 1994:9)

Thus, when selecting the input data, it is important that this data contains all the possible combinations of these input data points. For example the input data, as in holidays, working day or weekend, temperature, and all possible combinations of these factors have to be considered.

It is also important, that during the selection process to include weather turning points. For example, when the maximum temperature usually occurs in December, this data has to be included. Thus a careful study of previous weather data has to be conducted to select the best appropriate data.

To verify what the minimum of data required is, the verification technique as describe in previous paragraph is used. Once the NN is trained and it does not fulfil to the minimum specification, the process is stopped.

The next step is to use the baseline, which still adheres to the minimum verification criteria, to forecast the long-term impact of DSM in a region.

5.6 Long-term forecasting of DSM in a region

This section deals with the procedure involved in the estimation of the long-term effect of DSM on an hourly base.

5.6.1 Normalising the model

The first step in the long term forecasting is to normalise the model. Once the model has been verified against data it is unfamiliar with, and when the model baseline falls within the range of acceptable limits that are set, the model has to be normalised.

A whole year's of data is used to normalize the trained NN. This is crucial, because for the long-term forecasting of DSM the whole year's baseline is needed.



Normalisation means basically, adjusting the values of the baseline so that they are more representative for a typical or average year. This is divided into two segments, namely normalisation of the weather data and the schedules.

A Weather data

For the normalisation of weather data, the data is used to give a typical year's pattern that is representative of weather for the specific region under consideration. Currently there are various software packages or data sets available that have the ability to normalise the weather data.

For this investigation two normalisation models were found that could be used for this purpose, these are Meteonorm and CSIR typical data.

A.1 Meteonorm

Meteonorm is a computer-based program for climatological calculations, with an additional database containing comprehensive climatological data for various points on the globe.

The database contains measured, quality checked global radiation data for 1035 weather stations. Temperature data is available for 2409 stations. The weather stations are divided into 907 primary, 1502 secondary and 277 additional stations.

For the primary stations, most of the parameters listed below are available. For the secondary stations, global radiation is interpolated. Meteonorm utilized data from all the weather stations for the past ten years to calculate the weather profile for the specific weather station chosen.

The output file of *METEONORM* contains the following parameters for the monthly mean and for hourly data:

- Global radiation;
- Ambient air temperature;
- Humidity;
- Precipitation; and

- Wind speed.

A.2 CSIR Data

The CSIR published a set of data for a "typical" year. These sets are compiled from the most representative days over a measurement cycle of 30+ years.

In other words, if one considers for example 16 February, it may contain measurement data that were measured in 1962, whilst 17 February may contain measurements from 1975. The effect is a set of data that reflects the most probable weather occurrences or trends for each location.

One might feel that this "typical year" data takes the extremes out of the weather data, such as very hot summer days or very cold winter nights. This is true, but it makes the data more accurate in predicting the meteorological phenomena, because each day's data set represents the conditions that are most likely to exist on that specific day, based on a 30+ years of measurement history.

The dry bulb and wet bulb temperature was available for the following eighteen key locations only:

Table 5-2: Various key locations from CSIR

Cape Town	Jhb International Airport	Beaufort West
Port Elizabeth	Pretoria	Estcourt
Durban	Windhoek	Kimberley
Bloemfontein	George	Upington
Alexandebay	Matroosberg	Pietersburg
Keetmanshoop	East London	Maun

A.3



A.4 Conclusion

For the purposes of normalising the weather data, the weather data that gives an accurate representation of a "typical" year for that region. In choosing specific normalised weather data, it has to be remembered that the data has to give an accurate representation of that region and the weather factors that are used, has to be part of the output, otherwise these have to be generated.

Both the cases studied gave accurate enough results with all the data needed in this study. Meteonorm is chosen to normalize the data, as this software has more weather output parameters.

B Normalisation of holidays

The normalisation of the national holidays and specific holidays applicable for a specific region has to be considered.

To normalise the national holidays, the average weekday when a specific holiday occurred for the past 10 years was calculated. As the national holidays changed since the new government came into place, only the new set of national holidays were used.

The normalized data was then fed into the NN network and these results were then used to calculate the long-term effect of DSM on a region.

5.6.2 Calculations of the long-term effects of DSM in a region

The next step is to calculate the long-term effect of DSM for the region. The objective is to determine what the impact of a DSM option is for that region, with a ten-year economic life cycle. Eskom has a need not only to see the ten-year impact of the different DSM options, but also the hourly impact of the DSM options.

The first part of the simulation is to extrapolate the normalised baseline for a ten-year period. The second step is to add or subtract is to add or subtract any



buildings that will be constructed or demolished in foreseeable ten-year frame as illustrated in equation [5.12].

$$\text{New Baseline} = \text{Normalized baseline} \pm \text{Building} \quad [5.12]$$

The third part is to subtract the net effect of different DSM options from the new baseline.

$$\text{DSM baseline} = \text{New baseline} - \Delta \text{DSM option} \quad [5.13]$$

For the calculation of the impact of the DSM options, various techniques can be used depending on the accuracy that has to be achieved. In general, the more accurate estimations are the higher the cost. An agreement has to be reached on how much cost, thus time and resources is to be spent on the calculations of the DSM option. The output of the various DSM options has to be on hourly base.

The various DSM then can be evaluated using different evaluation indices. The analysed data then is used to determine which DSM option is the most viable for that specific region can then be chosen, as illustrated Figure 5-1

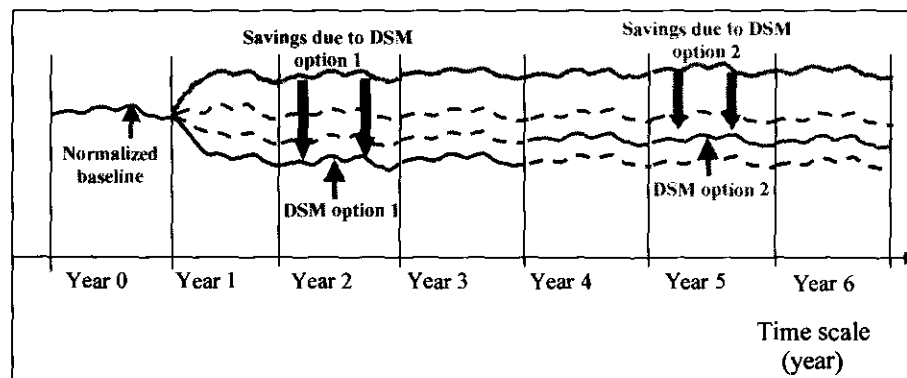


Figure 5-1: Long-term forecasting of DSM in a region

The following section describes how the impact of the DSM options are calculated.

5.6.3 Calculation of the impact of the DSM option

Schuldt (1998) reported that there are three alternative approaches available for estimating electricity savings. Their application varies with factors such as the objective of the analysis, complexity of the electricity system, measures of the electricity systems, the amount of the available end use consumption data and available resources. The following paragraphs describe these techniques briefly.

➤ **The test reference method**

The test reference method for savings estimations is most commonly used for new constructions. It requires the use of a paired test building that contains the conservation measures and a reference or a control building that does not.

Ideally the test and reference should be identical in all respects, except for the conservation measure. In practice this is not always possible, although an attempt should be made to select control buildings that are as similar as possible in terms of physical properties, construction type, age, orientation, occupation and occupant behaviour.

The test and reference buildings are calibrated separately to consumption targets that are prepared for each building type from utility billing records. Annual savings are calculated as the difference between the test and reference building.

The major advantage of this method is that savings are computed with respect to a completely independent control building, which is in no way influenced by the installed measure. The primary disadvantage of this approach is the added complexity and cost associated with data collection and analysis of the control building.

➤ **The before and after method**

The before and after approach is relevant to only retrofit construction. It requires the use of only a test building, which serves as its own reference. A calibrated simulation of post period consumption is prepared to reflect the baseline conditions of a selected pre-period. The difference in the post- and pre period

simulations are the effect of the conservation measures and other changes in the occupant behaviour.

The major advantage of this technique is that the electricity savings are based on two simulations that are fully calibrated to measured consumption. The primary disadvantage of this approach is that the simulations are performed over two different periods, with variations in weather and electricity system performance beyond the impact of the installed measure. The need for two separate simulations that must be adjusted, makes this method relatively costly in many cases. However, the cost will typically be less than that of the test and reference option.

➤ The Measure removal method

The measure removal method approach is useful for both new and retrofit construction. It includes a series of sensitivity runs with a fully calibrated post-period simulation that removes the effect of the installed measures.

The post-period calibrated simulation is prepared in the above-mentioned savings approaches. Each sensitivity run is prepared by changing simulation inputs relevant to measure performance to a condition that would most likely exist without the measure. Changes to the simulation are limited to parameters that are affected by measure performance.

This approach offers the advantage that adjustments for unrelated factors are not required as in the other two methods. The disadvantages of this approach are its assumption that measured performance is clearly defined and the inability to calibrate the baseline model of the single case studied. This reduces the confidence that the pre-period accurately represents the installed measures.

➤ Conclusion

Adjustment are often required in both the test and reference as well as to the before and after methods to correct for changes between the pre- and post periods that impact on the measure performance. These adjustments include items such



as weather conditions, occupant behaviour, production rates and physical properties.

All the savings estimation methods perform best when they are implemented with an engineering equation program such as Visual DOE. The rigor of an hourly simulation is required to implement the savings calculation techniques themselves.

Whatever technique is decided upon, the output has to be in an hourly format, so that it can be added or subtracted from the baseline.

5.6.4 Data conversion and analysis

To quantify the different options, the data first has to be in a form that it can be used in the calculations. This data then can be used for further analysis.

A Data conversion

For the data conversion the hourly data has to be integrated into a monthly and yearly basis. With this the maximum demand is determined for the different months. This data is then used to calculate the electricity cost using the tariff structure applicable for that specific region. This is done for the new baseline and the hourly savings that occur due to the DSM options.

The two data sets are then evaluated using various economic indices to determine which options is the most viable option for a specific case. The data sets are compared and evaluated to the specifications given by the client, to determine which options is the best for their application.

B Calculation of the amount of particles released

The mass of SO_x NO_x, particles and CO₂ that are released into the atmosphere due to the production of the electricity, are calculated for the different DSM options. The electricity use for the length of the economic lifetime is multiplied by a constant to obtain the different values.



Figure 5-2 illustrates the official TOU periods for 2002. The motivation of the TOU tariff structure is to encourage load shifting from peak periods to the off-peak periods.

In this study the TOU tariff structure is used as an indicative tool to determine the impact of the DSM options on the deferent time periods. Eskom treats national holidays as Saturdays and Sundays depending on the weekday they fall on.

The excel application written, divided the different hours in the applicable TOU tariff times, and calculated the cumulative electricity use for the these times. The national holidays were treated as normal weekdays. This resulted a slight decrease in accuracy, which was not worthwhile accounting for.

D Economic analysis

The various economic tools that are used to determine which options to install are:

- Capital expenditure;
- Discount rate;
- Internal rate of return (IRR);
- Net present value;
- Hurdle rate; and
- Simple payback period.

These concepts are briefly described.

The capital expenditure is the initial installation cost that the project will cost the investor to install this specific option.

The discount rate represents the cost of capital. This is analogous to the interest rate at which money can be borrowed from a bank or other financial institution. The different companies that finance the project will have its own set of standard.

Internal rate of return (IRR) is the interest rate received from an investment or project. A project with a capital cost of R 1000 and an IRR of 20 % is expected to

yield R 200 per year. It follows that a project should have an IRR that is equal to or larger than the discount rate to be economically viable.

Net present value (NPV) takes the time-value of money into account and presents the value in current year Rand. NPV takes up-front capital cost as well as expected future cash flow and inflation into account. Suppose a project has an initial capital cost of R 10 000, a simple payback period of 3 years and a NPV of R 20 000. The initial capital cost of R 10 000 might prevent this project from happening. Should this project not go ahead, the company who refused the project effectively lost R 20 000. This should only be allowed if the R 10 000 capital can be used on other projects with even higher NPV's.

IRR, NPV and discount rate is related in the following manner, a project with an IRR equal to or higher than the discount rate will have a positive NPV and will consequently be economical viable.

To manage risk and to ensure that only the most economically viable projects get funded, a hurdle rate is used. The rate is expressed as a percentage,

$$\text{Hurdle Rate} = \text{IRR} + \text{safety factor} \quad [5.14]$$

The hurdle rate is set high for projects involving a lot of risk and uncertain projects and can be much lower for "safer" projects. DSM projects are considered very "safe" projects and consequently do not usually have to pass high hurdle rates.

To determine which options to install, the investor has to have the ability to invest the capital expenditure for the project. For the investor to determine if a project is viable the IRR has to be higher than the hurdle rate set by the investor. In general the higher the IRR the better financial advantage the option provides.

Further analysis is done, by looking at the straight payback period and the NPV of the option. The straight payback period has to be smaller than a set standard. Usually in this industry this is approximately 3 years. Finally the NPV has to be as high as possible. If different options exist, the different factors have to be weighed

against each other, to determine the relative importance, and then a choice has to be made.

5.7 Conclusion

In this chapter the technique used to forecast the long-term impact of DSM in a region were described. Attention was given to what the properties of a good baseline is, how a baseline is constructed and refined using NN's. With this the verification standard that was used in this dissertation was discussed as well as what the set of standards are, to which the baseline has to comply.

As annual data is not always available a study was conducted to minimise the data sets used for the construction of the baseline. This aim was to reduce the number of data points in a practical way, without reducing the accuracy. Thus the verification test is used to ensure that the baseline could be used.

When a model is established with a high enough accuracy and with the least amount of data points, it has to be normalised that it can be used for the forecasting of the long-term impact of DSM in a region. Various economic indices were then discussed to evaluate the various options. From this the best options could be installed in that region. The next chapter will gives a brief background on the specific case study, this technique was tested on.

5.8 References

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6 Case study - Pretoria University

main campus

6.1 Introduction

The previous chapter described the technique how to forecast the long-term effect of DSM in a region. In this chapter the focus falls on applying this technique on a case study, namely the main campus of the Pretoria University. The chapter is divided into the following sections:

- Campus overview ⇒ A brief overview is given of the university campus, as to what type of buildings are found on the campus and there uses,
- Electrical overview ⇒ An overview is given of the electrical distribution network on the campus.

6.2 Campus overview

The Pretoria branch of the Transvaal University College (TUC) was forerunner of the University of Pretoria. It commenced its activities in 1908 with a staff of four professors and three lecturers. The University of Pretoria became a fully-fledged university in 1930. Currently the University has in total 10 faculties ranging from Engineering to Economic and Management Sciences.

With more than 32 000 students on campus, the University of Pretoria is not only the largest residential university in the country. Of this number, around 23 000 were undergraduates, and 9 000 were postgraduates.

The main campus of the University of Pretoria is situated near the business district of Pretoria. The campus has more than 60 buildings that covers an area of about 24 hectares.

The buildings have a wide variety of applications including hostels, lecturing facilities, offices, auditoriums, laboratories, canteens etc. The electricity use and occupation of the buildings depends on the usage of the specific buildings.

The city experiences a typical continental climate. Summer daytime temperatures average 30°C and during its sunny winter days temperatures may drop to 20°C, while winter evenings average at 6 °C. An annual rainfall of about 450mm mainly occurs during the summer months. Winds are moderate and snow during winter is extremely rare. The maximum summer temperatures are around 37°C while the minimum winter temperature may drop below freezing. The average annual ambient temperature is around 22°C.

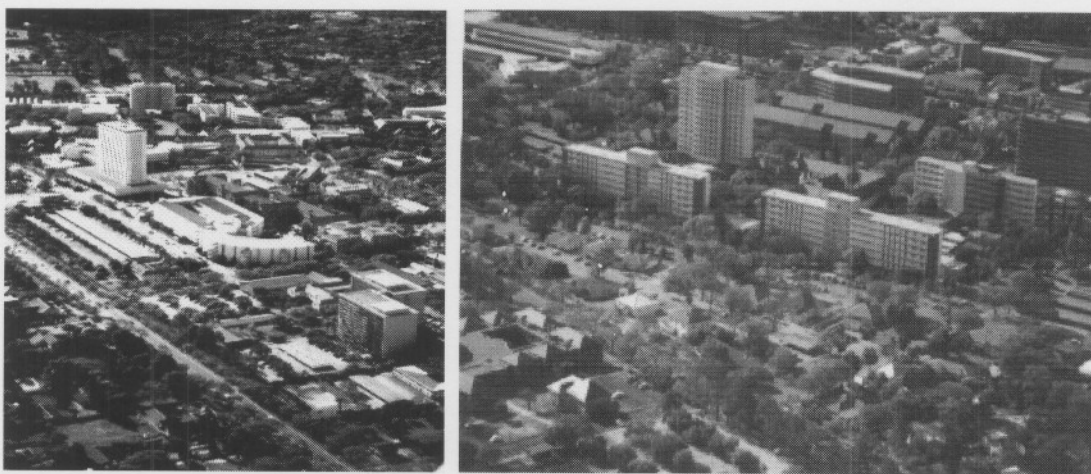


Figure 6-1: Bird's eye view of the Pretoria University main campus

The campus was billed in 1999 according to a two-part standard rate tariff structure (kWh electricity consumption and kW demand charges). The electricity consumption charge was 10.35 c/kWh VAT excluded. The demand charge was R 47.5 /kW VAT excluded.

6.2.1 Electricity network overview

The University of Pretoria is supplied by a three phase 11 kV connection from the local municipality. The supply is then distributed on the main campus of the University of Pretoria via four ring-networks and a single substation. These are the ladies' hostel ring, the east campus ring, the west campus ring, the north campus ring, and the humanities substation.

Electricity is distributed to the individual substations in each of these rings. The next level of distribution is the transformer that supplies electricity to the buildings and its systems.

Figure 6-2 illustrates the configuration of electricity and the distribution on the main campus of the university.

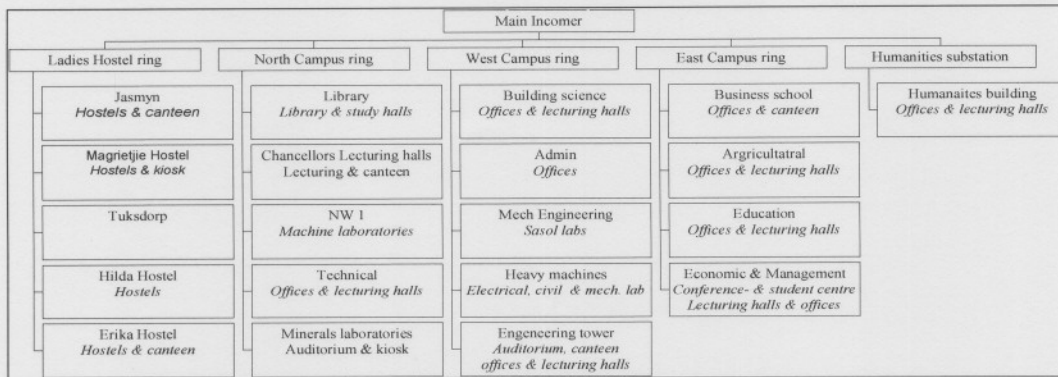


Figure 6-2: Electrical network of Pretoria University campus.

The use of each of the networks ranges from lecturing facilities, offices, hostels, cafeteria, canteen to machine laboratories.

7 Establishment of a baseline for the campus

7.1 Introduction

In the previous chapter an overview was given of the case study that was used for this dissertation. The focus of this chapter will be on applying the methodology to the case study, and indicate the results obtained

7.2 Establishment of the baseline with the aid of NN

7.2.1 Input and output variable

For the establishment of the baseline hourly data for the period 1 Jan to 31 Dec 2000 was used. The input variables for the NN were

- Date
- Time of day
- Day type, the specific day type (weekday or weekend)
- Holiday (national as well University of Pretoria campus holidays)
- Weather conditions ⇒ among them were:
 - Outdoor air temperature
 - Outdoor relative humidity
 - Solar radiation
 - Wind speed

Most of the datasets are quantitative variables but some datasets such as the day of the week, are categorical data and these have to be encoded to numerical values. Encoding changes data from a single data-point with any dimensionality to multi data-point with binary dimensionality.

For the output the electricity usage for the main feeder at the campus was used. The weather data was only available on an hourly basis. This resulted in that one could either integrate the electricity use data, or interpolate the weather data. Because of simplicity it was decided to take the first approach.

7.2.2 Data collection

The data for the simulation of the NN networks were collected from actual measurements.

- *Date, & day type.* Actual calendar months for the time of investigation were used.
- *Holidays.* The dates for the holidays for the campus were obtained from facility personnel.
- *Weather data.* Actual weather conditions from the Pretoria weather station were obtained. The weather data for the same period from Jan. – Dec. 2000 were used.
- *Simulated data.* Actual measured consumption for the University of Pretoria was used as output target for the NN program. The data was obtained from the university for the months of Jan. – Dec. 2000

7.2.3 NN set-up and topology

The following section discusses the NN topology used during this study.

Various combinations of factors that influence the result of the NN were investigated. These factors can be divided into three broad categories. The different categories and its different options are listed below.

- Input data
 - Weather data, day and day type, holidays etc.
 - Encoding of data
- NN Topology
 - Transfer function
 - Number of hidden layers
 - Number of hidden neurons or units per layer
- Learning criteria
 - Stop criteria (Number of epochs before the training stopped)
 - Momentum
 - Learning rate

For the input variables, the refinement strategy used to determine the best combination of variables, a top down structure was used. Different combinations of weather data as well as the encoding of the different variables were investigated.

For the NN Topology, a Sigmoid function was chosen. As the selection of the number of hidden neurons for a layer is an art rather than a science, it was decided that the number would be left as chosen by the software used. Finally only the number of hidden neurons can vary in the NN Topology. For the NN topology a bottom up strategy was adopted.

For the learning criteria the momentum and learning rate influence the local minimum found. It was decided to keep these variables as they were chosen by the software. Only the stop criteria were adjusted to determine the minimum number of epochs that were needed to train the NN successfully.

The variables that could be varied in the training of the NN is given in Table 7-1

Table 7-1: Training matrix table

Option	1	2	3	4
Encoding of data	Month	Day-type	Day	Hour
Input variables	Outdoor air temperature	Outdoor relative humidity	Solar radiation	Wind speed
Number of hidden layers	1	2	3	
Stop criteria	10 000	20 000		

A full factorial study could be used to determine the impact of the various variables on the result. A total of 48 runs would then be needed. A simpler approach was taken, firstly all the data is used, and then the simplest topology was found that meets the set requirements. When it was established which topology is the best,

the variables were then reduced, to determine the minimum of factors that could be used. Table 7-2 illustrates the approach taken for the first number of iterations.

Table 7-2: Approach used to determine the best network topology

Run	Data encoding option	Data option	Number of hidden layers option	Epochs option
1	1,2,3,4	1,2,3,4	1	1
2	1,2,3,4	1,2,3,4	2	1
3	1,2,3,4	1,2,3,4	3	1
4	1,2,3,4	1,2,3,4	1	2
5	1,2,3,4	1,2,3,4	2	2
6	1,2,3,4	1,2,3,4	3	2

Once the best NN topology and number of epochs were established, the number of data point were reduced. As the outside temperature and relative humidity are main factors that influence the electricity consumption of buildings, a factorial study of the solar radiation and wind speed was performed to determine which had the largest influence. Table 7-3 illustrates the approach used for the refinement of the different input variables.

Table 7-3: Refinement strategy used for input variables.

Run	Data encoding option	Data option
7	1,2,3,4	1,2,3
8	1,2,3,4	1,2,4
9	1,2,3,4	1,2
10	1,2,3	1,2,3
11	1,2,3	1,2,4
12	1,2,3	1,2
13	1,2	1,2,3
14	1,2	1,2,4
15	1,2	1,2
16	1	1,2,3
17	1	1,2,4
18	1	1,2

7.2.4 Results and verification of the baseline model.

A Introduction

The models were trained on annual hourly data for the year 2000. For the verification a complete independent data set was used. For the verification of the data it was decided that 1998 data was to be used, as this data was the most intact of the data that was available.

For 1998, two of the three incoming lines measuring devices were down for the first three months, as these two loggers did not record any data. Consequently for verification of the data April to December month's data were used.

The next section compares the results by using the CV(RMSE).

B Comparative results

To compare the different cases, the CV(RMSE) of the hourly data is used as a guideline. This indicator evaluates the hourly data ensuring that the errors do not cancel out each other.

Figure 7-1 illustrates the results of the factorial study of the NN topology.

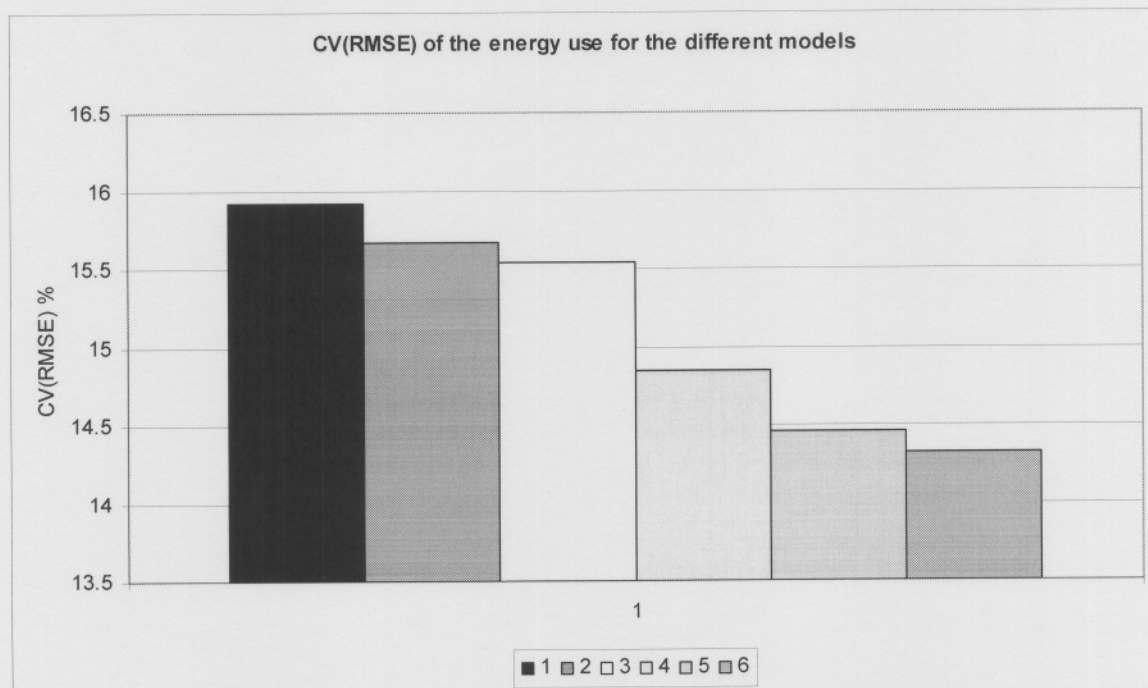


Figure 7-1: CV(RMSE) for model 1 to 6

From Figure 7-1 it can be seen that in general, the more levels are used, the accuracy of the NN model output increases. Secondly, the longer the NN can train, the accuracy also increases.

Thus, it can be concluded that the best results are obtained with three hidden layers and a higher number of epochs. This confirms the observation made by Aldrich that the higher the number of hidden layers, the higher the accuracy. Model 6 NN topology was adopted as the NN that was giving the best results and was used further as the base for the refinement of the input variables.

The drawback of this technique is that, the more hidden layers and more epochs are used, the longer it takes to train the model. For example, it took approximately 50 hours for model 6 to train, whilst it took only 22 hours for model 1 to train. Despite this drawback, the advantages of the increased accuracy, overshadow the disadvantages.

Figure 7-2 indicates the results obtained from the factorial study of the input data.

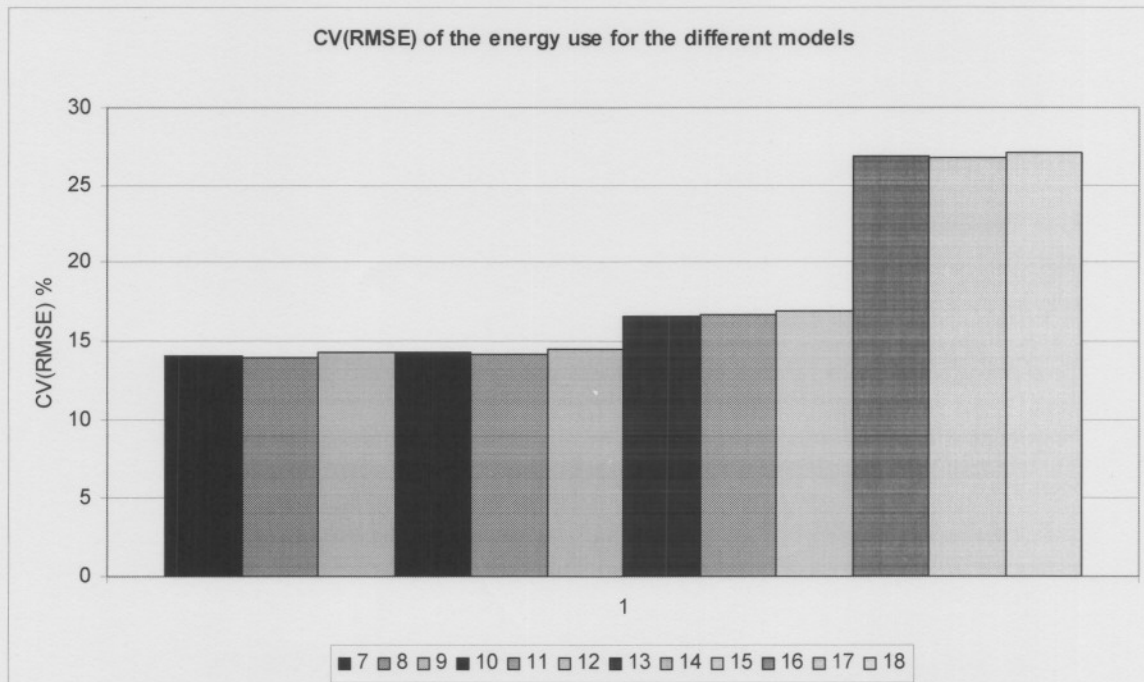


Figure 7-2: CV(RMSE) for models 7 to 18

From Figure 7-2 it can be observed that the decrease of the weather variables does not dramatically decrease the accuracy of the result. In general it seems that the use of sun radiation gives a better result than that of the wind speed.

Secondly it is observed that the encoding of the hour and the days does not have a large positive impact on the accuracy. By using these two data points as encoded data, fifty-five data points are added, that need to be solved. This increases the complexity of the matrix that is to be solved, and which does not give a better result.

Finally it is observed that the month and the weekday type have at least to be encoded. This is because the weather patterns change from month to month and the electricity use pattern also changes, depending on what weekday type it is. These factors have a stronger effect on the electricity use than the day of the month and the time of the day.

C Statistical results

The objective was to find the simplest model that still fulfils the requirements of the verification study. Model 15 has the least amount of data points, and still gives adequate accurate enough results. Consequently this model's detail verification results are shown in Table 7-4.

Table 7-4: Comparison values of the errors for the main feeder

Description	Time period	Comparison tool	Abs value	Limit
Electricity use	Hourly data	MBE hourly	7.82%	< 10%
		CV(RMSE)hourly	16.25%	< 25%
	Monthly data	ERR monthly	3.50%	< 15%
		ERR year	3.12%	< 10%
		CV(RMSE)monthly	3.84%	< 10%
	Monthly data (Sub system)	MBE monthly	1.43%	< 7%
		CV(RMSE)monthly	14.26%	< 15%
Max demand	Monthly data	ERR monthly	10.23%	< 15%
		ERR year	4.56%	< 10%
		CV(RMSE) monthly	6.59%	< 10%
Electricity cost	Monthly data	ERR monthly	13.28%	< 15%
		ERR year	3.58%	< 10%
		CV(RMSE) monthly	4.32%	< 10%

The table indicates that the ERR Monthly for the Electricity cost and the CV(RMSE) monthly calculation for a subsystem are the two values closet to the limit. The CV(RMSE) monthly for the subsystem is less than a percent in the range of the limit, but is still beneath the limit. It could be argued that these values are too close, but the indices indicated are calculated from the data for 1998, which the NN has not been trained on.

The best result measured was for the MBE monthly calculation, which falls way below the limit.

In general, all the values fall beneath the limit set and thus this modelled baeline could be used for further purposes.

The next paragraph discusses the graphical results in order to give a visual impression of the obtained results.

D Graphical results

The graphical results of the energy use, maximum demand and energy cost are first shown for a single week, then for 4 months of the year on an hourly basis as well as the integrated results on a monthly basis.

D.1 Weekly comparison

The figure below demonstrates the result of the simulation data against the actual data for a single week in October.

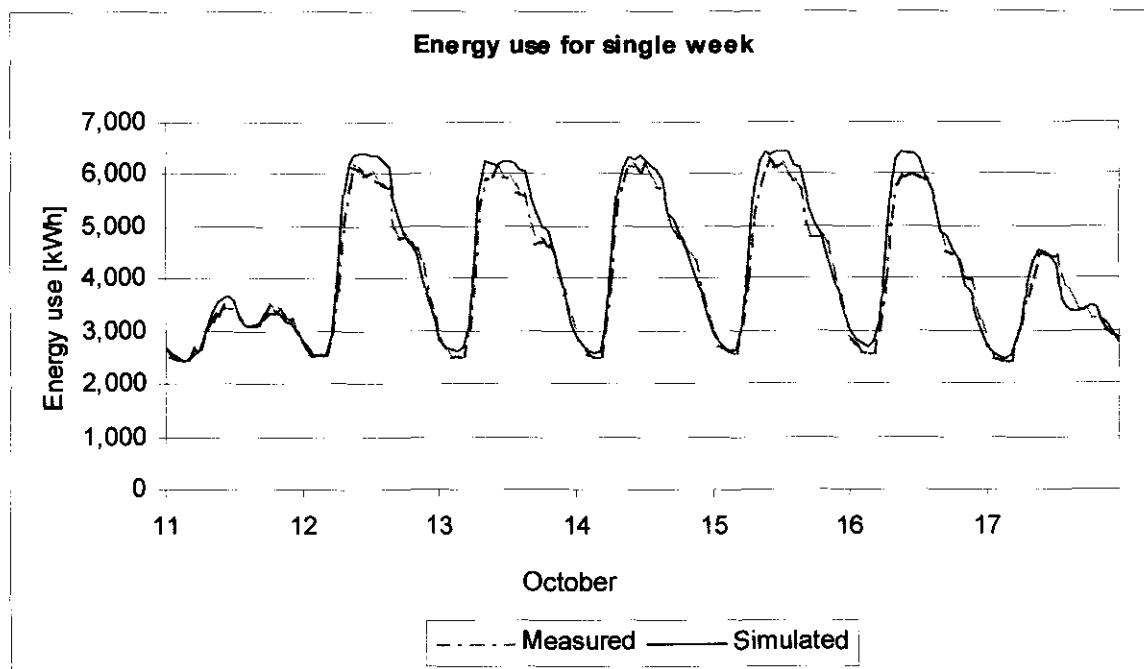


Figure 7-3: Comparison for a single week for 11-18 October

It can be observed from Figure 7-3, that NN in general follows the measured energy use relative closely. In general the NN model overshoots the maximum demand of the day and has difficulties to follow any abrupt changes in the energy profile. These changes usually occur due to random behaviour of the occupants.

Due to the high diversity of the campus, the random behaviour of the occupants has a smaller impact on the energy use profile. The energy use is also measured at a high distribution level, which includes a high number of buildings that have a fixed building schedule. The fixed building schedule simplifies the learning process and aids the close relationship that is observed.

D.2 Monthly comparison

The figure below demonstrates the result of the simulation against actual data for four different months, for the different seasons of the year. The months shown are: May, July, October and December 1998

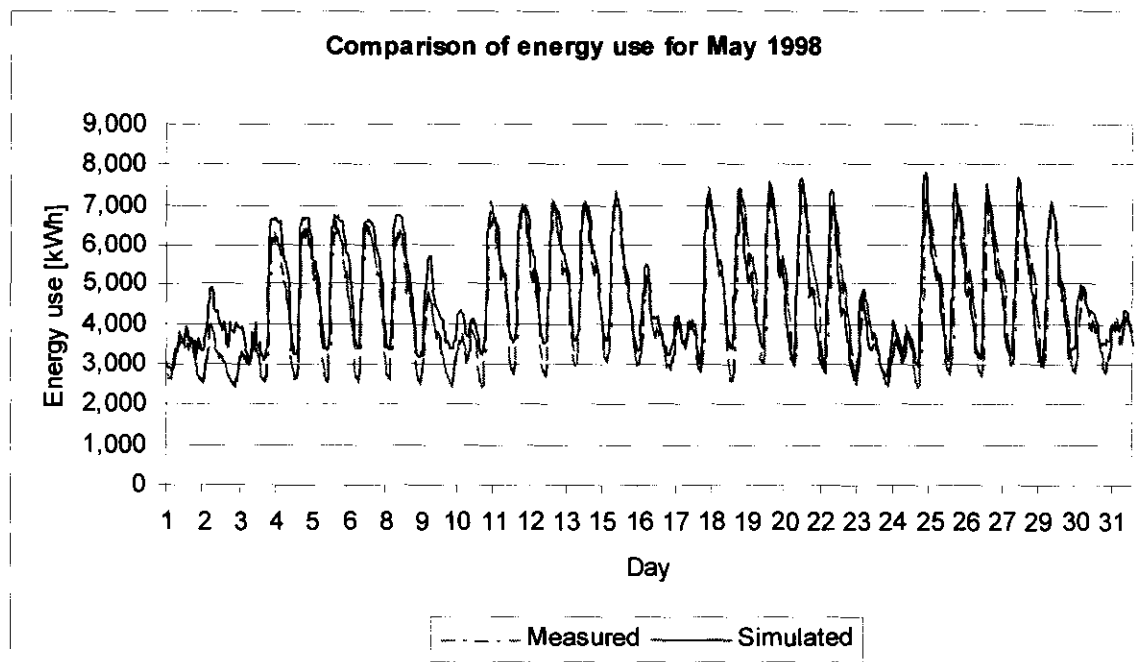


Figure 7-4: Hourly comparison for May 1998

The hourly comparison for May illustrates that the NN could follow the energy use profile accurately. It seems the NN had some problems following the energy usage measured for the long weekend of 1 to 3 May. The NN interpreted the energy used on 2nd of May has a different profile and larger values than that of the actual energy use measured.

For the first week the simulated energy use was slightly higher during the peak hours than that of the actual energy use. The figure also indicates that the minimum daily energy of the simulated model is higher than the actual energy use.

These observations should not be a problem, depending on the client's needs. For example, Eskom is more interested in daily maximum demands, thus the daily minimum errors that are observed are not of a major concern. Furthermore, because the long weekend's energy use is much lower than the rest of the time, this error is not a great concern.

The errors observed could be attributed to the fact that the data the NN used, gave these results under 'trained' conditions. The NN 'learns' from example, thus the example given for the input parameters gave such a result.

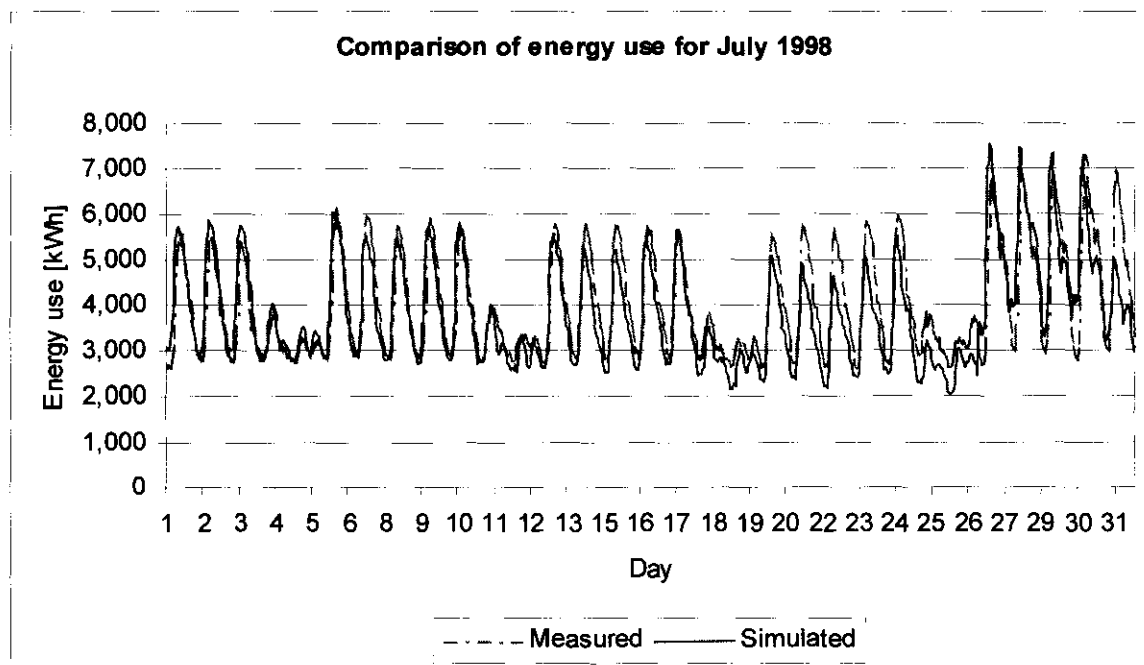


Figure 7-5: Hourly comparison for July 1998

The hourly comparison for July illustrated that the NN could follow the energy use profile accurately. It seems the NN had some problems for the week of 20 to 27 July. The NN interpreted that, for these days, the simulated energy used late in the day is lower than of the actual energy use. This is a rare event, and is not often seen for the remainder of the data.

The errors observed could be attributed to the fact that the energy use for these conditions obtained from the trained data, gave a smaller energy use. The NN learns from example thus the example given for the input parameters gave such a result.

This would probably be of concern for the client, as most of the time this has an effect on the maximum demand of the month. As this was during holiday time, the campus was not experiencing a monthly maximum demand. Thus this error is of lesser importance.

Secondly the NN model could follow the abrupt increase in the energy use of the campus. This increase was due to the University starting on 27 of July, with the students returning.

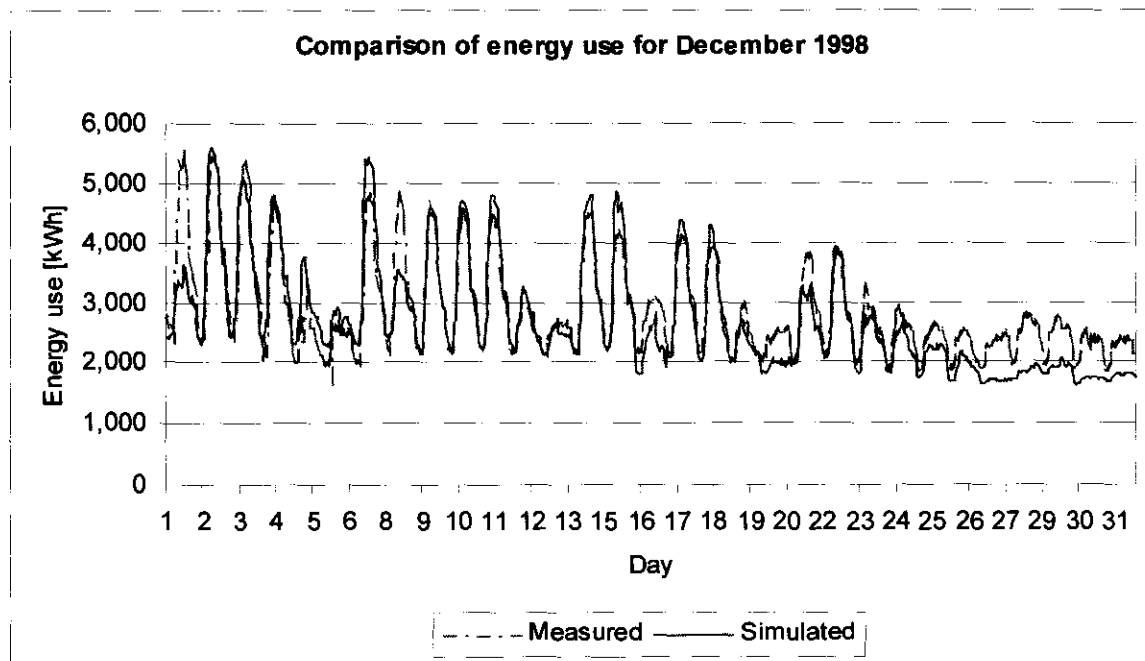


Figure 7-6: Hourly comparison for December 1998

The hourly comparison for December illustrated that the NN could follow the energy use profile fairly accurately. The simulated model did not follow the actual data very closely for the first and eighth of December. The NN interpreted that, for these two days, the simulated use is much lower than that of the actual energy use. This is a rare event and is only seen on these two dates.

It is also observed that the simulated energy use followed the decrease in the actual energy for the 16th of December, which was a national holiday. A dramatic decrease in the energy profile was observed from the 20th of December, as fewer people occupied the campus during this time. The NN could follow the trend relatively accurately, but seemed to interpret that for 25 December onwards the energy use should be less than was the actual case.

The errors observed could be attributed to the fact that the energy use for these conditions obtained from the trained data, gave a larger energy use. The NN learns from example thus the example given for the input parameters gave such a result. No apparent reason could be found from the trained data to suggest why this phenomenon occurred.

This should not be a problem, as the campus energy use during the holidays decreases, and it thus has a smaller impact on the maximum demand of Pretoria or South Africa.

D.3 Yearly comparison

The figures below demonstrate the results of the simulated data against actual data for energy use, maximum demand and energy cost for the period of April to Dec. 1998

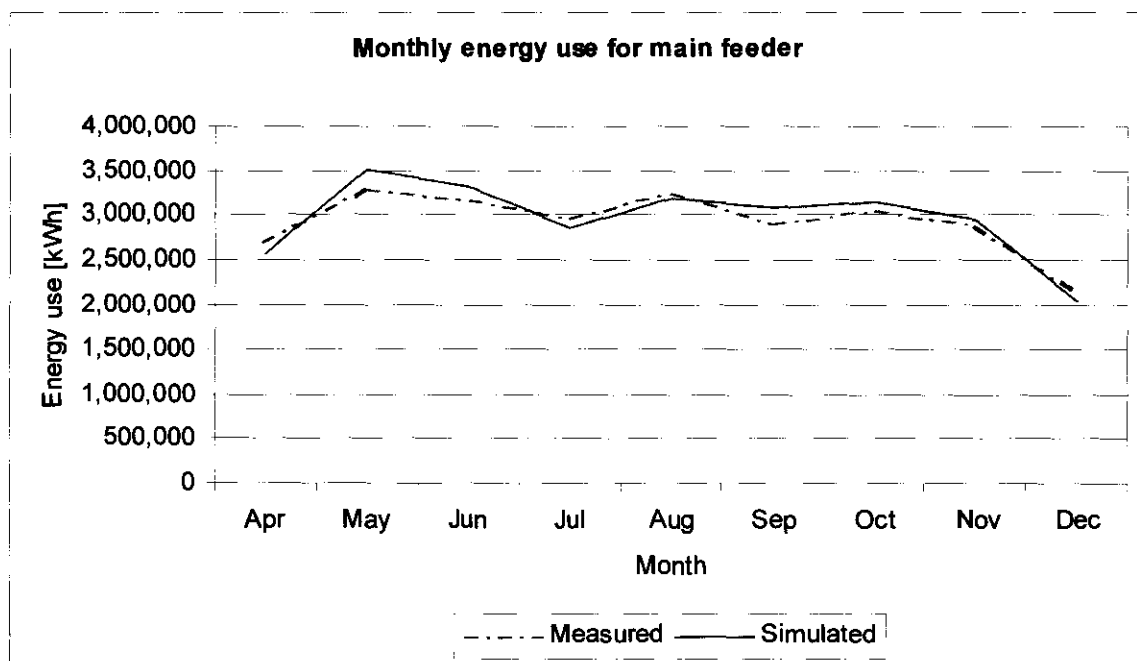


Figure 7-7: Energy use comparison for April - Dec. 1998

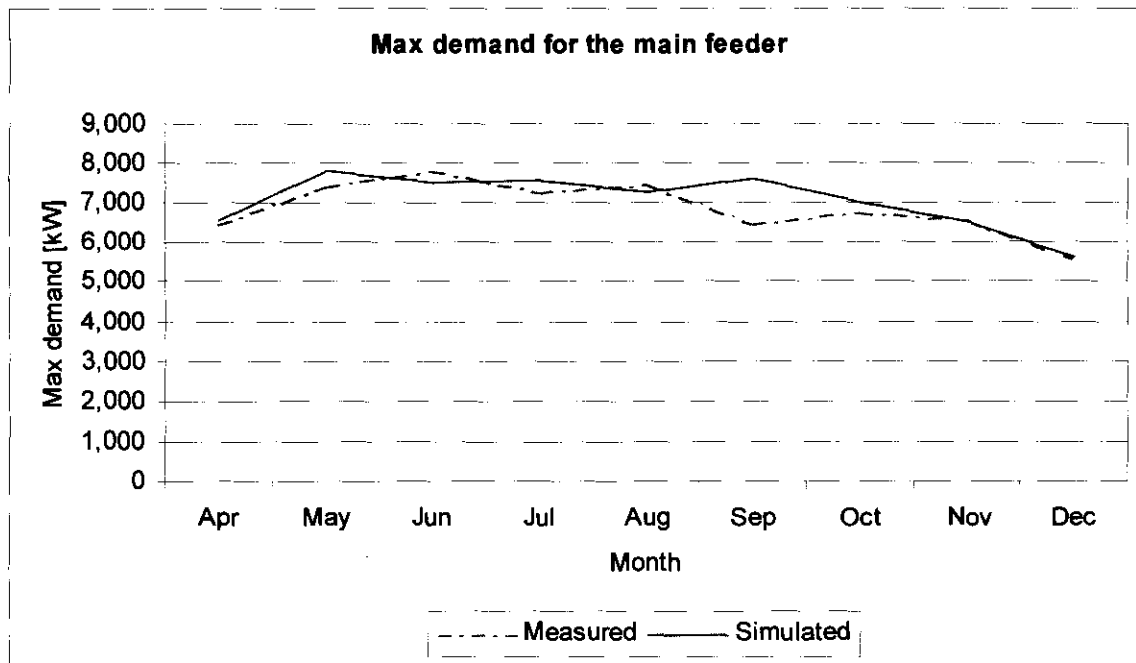


Figure 7-8: Max demand comparison for April - Dec. 1998

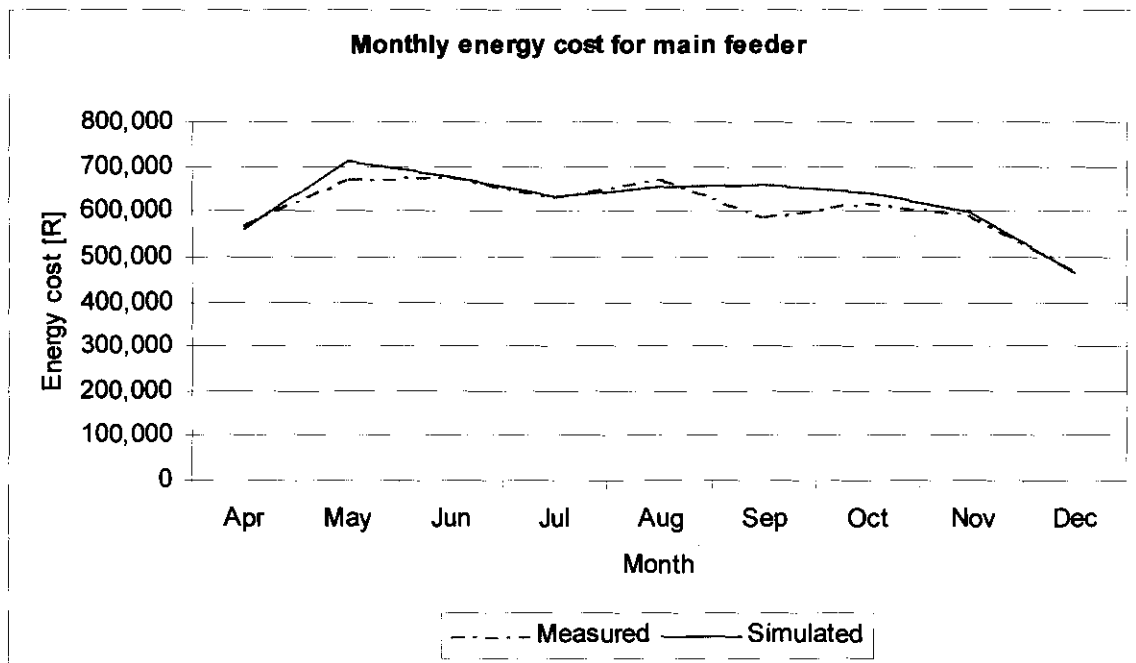


Figure 7-9: Energy cost comparison for April - Dec. 1998

Figure 7-8 indicates the simulated energy use following that of the actual energy use very closely. The largest differences are observed for the months of May and September. The errors observed still comply with the verification guidelines.

Figure 7-9 indicates that the simulated model was fairly close in predicting the maximum demand. The largest difference is observed for September. Maximum demand measurement is based on the maximum hourly reading that occurred in that month. Thus, a small error on the hourly profile could have large impact on the maximum demand of that month.

Figure 7-9 illustrates that the modelled energy cost also followed the actual energy cost fairly closely, with September having the largest error. This is because a large part of the energy cost is influenced by the maximum demand, thus showing the strong resemblance.

7.3 Conclusion

From the results shown, it can be concluded that:

- The NN can be used successfully to model the energy profile of a region, with little knowledge of the underlying installed system that has an influence on the energy consumption of the system. This is demonstrated by the fact that the verification of the data adheres to all the indices that are given. The data used for the verification is for 1998, and the NN model did not train at all on this data.
- The NN has some difficulty estimating the maximum demand of the month. This is because the maximum demand occurs only once a month, thus a small error on the hourly profile could have a large impact on the maximum demand of that month.
- The NN seems to underestimate the energy use for national holidays. This should not be a big problem, because in general, national holidays don't have a large impact on the national energy use. The savings of the DSM options are thus also much smaller on these days.
- The NN seems to have difficulty in following the energy use profile for events where there are national holidays within university holidays. This should not be a problem, because the energy use for that period does not change very much, resulting in having a small impact on the regional or national maximum demand.

- The NN seemed not to follow the minimum energy use for the mornings, during the month of May. This should not be a major concern in most cases depending on the client's needs. For example, Eskom is more interested in the peak demand of South Africa, thus this phenomena should not be a great concern.

From the training of the data it could be concluded that:

- In general it can be seen that the higher the number of Epochs, the more accurate the results are for the case studied.
- The more hidden layers used in the NN topology, the higher the accuracy of the network.
- The data had to be encoded in order that the NN could find the relationships between the inputs and outputs. This was done for both the month and day types.
- By using encoded data for the day of the month and the hour of the day, the accuracy did not dramatically increase. By encoding the day of the month and the hour of the day, the number of data points are dramatically increased, which in return increases the number of neurons and unknowns that have to be solved. Although the NN manages to learn with the increased number in data points, the results are not significant enough to indicate a clear advantage of using these encoded data points. Thus only the month and weekday types are adequate enough.

It can thus be concluded that NN can be used successfully to model the energy use of a region with a high diversity in use. This was illustrated by a case study of the main campus of the University of Pretoria. The major drawback of this technique is that hourly data for the whole year is needed to train the model. The question arises as to just how much data is needed to train the model on, to still generate accurate results. The following section answers this question.

8 Minimizing the data points

8.1 Introduction

In the previous section NN were tested and proven to be a handy tool for the establishment of an hourly baseline. This baseline could then be used for the long-term forecasting of the impact of DSM in a region. The main reservation with this technique is that hourly data for a whole year is needed to train the model. The question arises as to what the minimum is to train the data on. The focus of this section will be to determine exactly how much information is needed to establish an accurate enough baseline that adheres to the given parameters.

For the reduction in input data, the NN still has to learn from the available data what the relationships are for all the cases encountered. In other words, if for example, weather and holidays have an influence on the model performance, the NN has to be learned where data contains both of these factors. The study undertaken, was to determine exactly how much of this information is needed to model the data with usable accuracies.

Before a study can be conducted, it has to be pointed out, that gathering data is a sequential process. Therefore it is pointless to conduct a study, for example where data is collected only every first week of the month, while the rest is left out. The measuring time may be shortened, but the time to collect the data is still the same.

A better option is to select the data sequentially, but to reduce the measuring time from for example, a full year of data to only 6 months of data.

8.2 Procedure for minimizing the data

Firstly the data has to be examined to determine which data is the most important data, that needs to be included in the minimizing of the data points. By examining the data one can choose the best datasets, so that the NN receives the relevant information to train on.

When examining the weather data from previous years, it was noticed that the coldest months are around June and July. The coldest days were experienced during June and July.

The hottest months of the year are in some cases, January, February and March, whilst in other cases they are October November and December (based on the percentage of hottest hours per month). Finally, from the data examined, it was observed that the hottest day of the year most frequently occurred in November.

It was also observed that the turning point of the season is usually around June or July for the winter and December or January for the summer.

Finally Table 8-1 indicates actual data that was collected for the holidays in the year 2000. The purpose of including the table is to use it as an indicator, in order to ensure that the month's chosen include holidays, so that the NN can learn from this data.

Table 8-1: The number of national holidays and university holidays at the University of Pretoria for the year 2000

Month	Percentage of hours above 30°C	Percentage of hours below 5 °C	National Holidays	University of Pretoria Holidays
January	68		1	29
February	73			
March	67		1	8
April	45		3	2
May	18	15	1	
June		45	1	9
July		60		16
Aug		80	1	
September	23	13	1	5
October	35			2
November	56			
December	67		3	24

It was decided to test the concept that at least the turning points need to be included, through the elimination of a month at a time. This was done until the NN could not successfully model the energy use of the campus using the verification criteria described previously.

8.3 NN Topology

The NN topology used in the training of the NN, is one with three hidden layers and with 20 000 epochs.

8.4 Results and verification of the baseline model.

8.4.1 Introduction

The results of the trained model is verified against a complete independent data set. The NN model was trained on data for the year 2000, and was verified against data for 1998.

For the verification of the data it was decided that 1998 data is to be used, as this data was the most intact of the data that was available. For 1998, only data from April to December was available.

The next section gives the comparative results of CV(RMSE) obtained during this study.

8.4.2 Comparative results

To evaluate the different cases, the CV(RMSE) of the hourly data is used as a guideline. This indicator evaluates the hourly data ensuring that the errors do not cancel out each other.

Figure 8-1 illustrates the results of the two models trained.

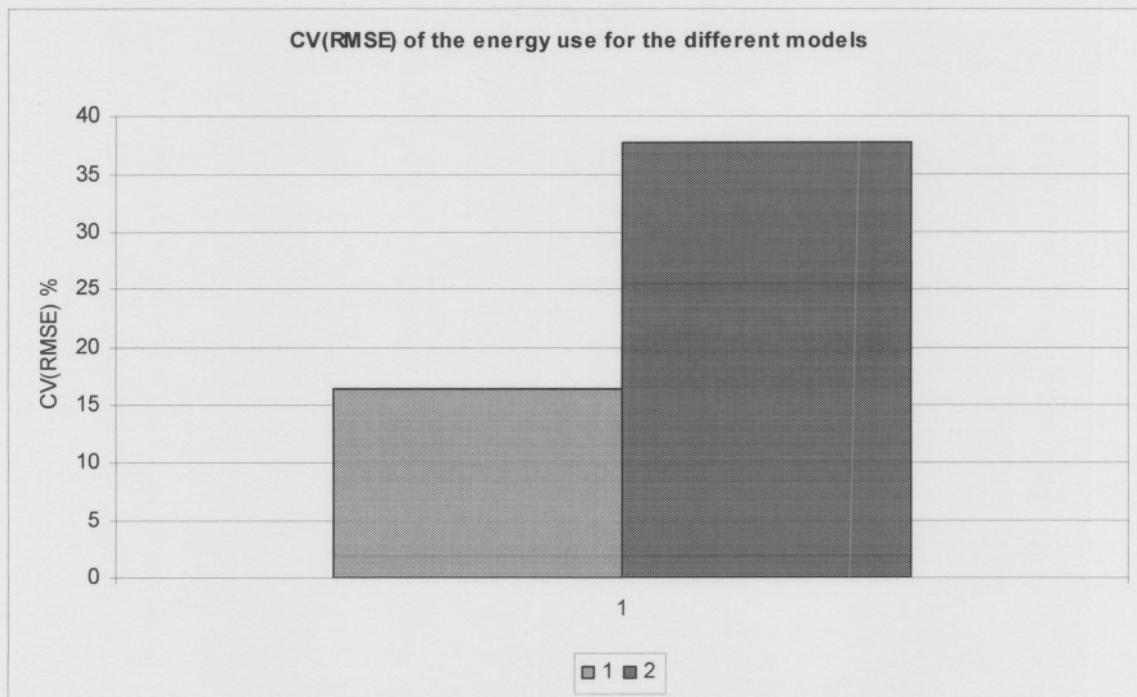


Figure 8-1: *CV(RMSE) for model 1 to 2*

From Figure 8-1 it is observed that as soon as one month is deleted from the input data, the NN could not obtain the minimum set of requirements. This result did not change for the by choosing a different month. The NN topology was subsequently also changed, for more layers, but this did not have a very positive effect, as expected.

The next section illustrates the statistical detail results obtained.

8.4.3 Statistical results

The detailed verification result for this model is shown in Table 8-2.

Table 8-2: Comparison values of the errors for the main feeder

Description	Time period	Comparison tool	Abs value	Limit
Energy use	Hourly data	MBE hourly	31.8%	< 10%
		CV(RMSE)hourly	37.8%	< 25%
	Monthly data	ERR monthly	31.8%	< 15%
		ERR year	7.0%	< 10%
		CV(RMSE)monthly	8.8%	< 10%
		MBE monthly	6.2%	< 7%
Max demand	Monthly data	CV(RMSE)monthly	17.0%	< 15%
		ERR monthly	20.2%	< 15%
		ERR year	6.9%	< 10%
		CV(RMSE) monthly	8.1%	< 10%
Energy cost	Monthly data	ERR monthly	25.6%	< 15%
		ERR year	6.4%	< 10%
		CV(RMSE) monthly	7.8%	< 10%

The table indicates that six of the indices that do not comply with the minimum set of standards set. The largest error was the CV(RMSE) using hourly data.

The table indicates that the annual error and CV(RMSE) for a monthly time period comply to the set of standards. It is of greater importance that hourly data should comply with the verification criteria, therefore this model is unacceptable.

The following paragraph graphically illustrates the results for the month in which the data was not used to train the NN.

8.4.4 Graphical results.

The results for December 1998 are shown graphically, to demonstrate what happens for December when the data was removed to give an indication of how the model struggles to display information which it was not trained on.

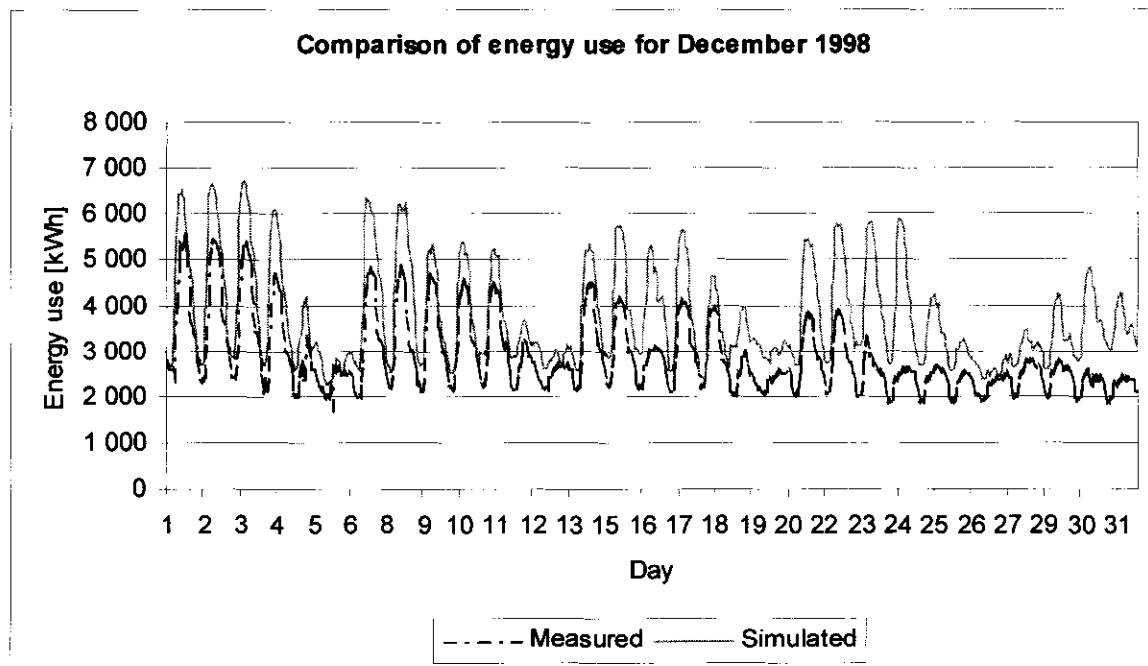


Figure 8-2: Comparison of the energy use for December 1998.

Figure 8-2 illustrates that the NN model interpreted from the input data that the energy use for December should have been higher. Furthermore, the NN model could not interpret that 16th December was an actual holiday, although the model learned the energy use for other holidays.

Finally it could also be seen that the NN could not follow the trend of when the energy use decreased from the 20th of December.

8.4.5 Conclusion

The major cause for these errors is that one of the encoded inputs is the number of months. The NN did not have the data for December as input, therefore in the verification of the data it was not recognised. Thus the NN encountered a new parameter, which it has not seen before.

This phenomenon illustrates the fact that NN learn from examples and cannot extrapolate very well, when the data has not been “seen” during the training period.

A possible solution to the problem is to test whether the seasons could rather be used instead of the months. Thus, if the NN encounters data in December, it would already be familiar with this data as it is part of summer.

The following section investigates this possibility.

8.5 Modelling the baseline using seasonal data.

8.5.1 Introduction

It was found that the baseline could accurately be modelled using encoded months as one of the inputs. The problem with this concept is that annual data is needed. Therefore, a whole year had to pass before any results could be obtained. Consequently, a study was performed dividing the year up into three seasons. These seasons being summer, winter, as well as autumn and spring combined.

To distinguish in which season Pretoria actually experiences, the guidelines of the weather bureau for the known season were used. This was extended by examining the temperature and changing the dates, to suit the impact of the first cold front that was experienced.

8.5.2 NN set-up

Table 8-3 describes the NN topology used for the training of the baseline.

Table 8-3: NN topology used during training

Input encoded data	Season, Day of the month, Weekday, hour
Input data	Temperature, wind relative humidity, radiation
Number of epochs	20 000
Number of hidden layer	3

8.5.3 Results and verification

A Introduction

The models were trained on annual hourly data for the year 2000. For the verification a complete independent data set was used. For the verification of the data it was decided that the 1998 data was to be used, as this data was the most intact of the data that was available.

For 1998, two of the three incoming lines measuring devices were down for the first three months, as these two loggers did not record any data. Consequently, for verification of the data, April to December month's data was used.

Unfortunately by using the season the baseline could not be successfully established. The best results obtained from the study are shown statistically.

B Statistical results

Table 8-4 illustrates the best values obtained during the study.

Table 8-4: Comparative values of the errors for the main feeder

Variables	Time period	Comparison test	Abs value	Limit
Energy use	Hourly data	MBE hourly	19.8%	< 10%
		CV(RMSE)hourly	31.7%	< 25%
	Monthly data	ERR monthly	19.8%	< 15%
		ERR year	7.5%	< 10%
		CV(RMSE)monthly	8.1%	< 10%
	Monthly data (Sub system)	MBE monthly	6.8%	< 7%
		CV(RMSE)monthly	21.2%	< 15%
Max demand	Monthly data	ERR monthly	22.7%	< 15%
		ERR year	11.6%	< 10%
		CV(RMSE) monthly	12.4%	< 10%
Energy cost	Monthly data	ERR monthly	18.2%	< 15%
		ERR year	9.3%	< 10%
		CV(RMSE) monthly	9.8%	< 10%

The table indicates that eight of the indices do not comply with the minimum set of standards set. The largest error was the CV(RMSE) using hourly data.

The table indicates that eight of the indices do not comply with the minimum set of standards set. The largest error was the CV(RMSE) using hourly data, and the smallest error was for ERR year.

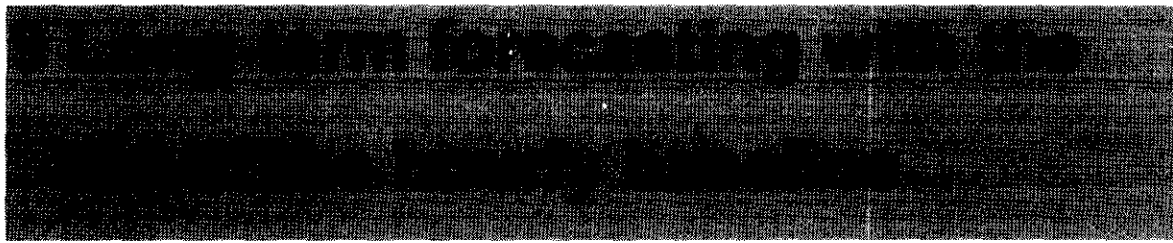
The table indicates that the ERR year and CV(RMSE) for the monthly time period did comply with the set of standards. It is of greater importance that hourly data needs to comply with the set of standards, thus the model is unacceptable.

Thus this model used all the encoded data possible and input data that was available, but still did not comply with the verification criteria. Thus the NN could not 'learn' the relationship from the data presented.

8.6 Conclusion

From the above presented in this chapter, it can be concluded that:

- NN needs at least a whole year of hourly data to learn the energy use of the campus for the case where the months are encoded. When this time was shortened by one month, the NN could not successfully interpret the data, in order to construct a baseline.
- The NN has difficulty in modelling the data that it had not trained on. During the set-up of the original model the months were encoded as input data. By minimising the number of months, the NN encountered a new parameter, which it has not seen before.
- For the unfamiliar data the NN estimated a larger energy use for the period not learned on. The NN could also not follow the energy use for a holiday, even though it was trained on numerous holidays, in the summer season.
- The phenomenon illustrates the NN cannot extrapolate very well, especially if the data has not been encountered before.
- By dividing the year into three seasons, and training on all the possible weather data still did not give accurate enough results that could be used for modelling the energy use of the campus.



9.1 Introduction

In the chapter 7 it has been established that NN's can be used with great success to model the energy use of the University of Pretoria main campus. In chapter 8 it was also determined that with the technique used, little to nothing could be done to reduce the amount of data. This sections focus will fall on forecasting the impact of DSM with a ten-year life cycle.

To illustrate impact of the impact of DSM options, the simplest baseline explained in chapter 7 was chosen. Actual results energy audit that was performed in the main campus of Pretoria University, is used to illustrate the potential ten-year impact of the DSM for a ten year-life cycle.

9.2 Normalization of the baseline

The first step is the normalization of the trained baseline. The normalization of the data is divided into two parts, namely the normalization of the weather data and the normalization of the regional and national holidays.

For the normalization of the weather data Meteonorm program was used. An outset file was generated, that gives the normalized weather date for Pretoria. For the campus holidays, the average time period and the weekdays when holidays occurred were taken. The same was done with the national holidays.

The NN was fed with this information in order to calculate the normalized energy profile for the university of Pretoria using the simplest model that still accurately enough simulated the actual energy use. Model 15 in chapter 7 was chosen for this purpose. The model used the outside temperature, relative humidity, encoded month as well as encoded day type as inputs. The NN topology was set for three hidden layers. The NN trained up to 20 000 epochs.

The normalised baseline was then copied into an Excel spreadsheet, from where all the calculations were done. The graphical and numerical results obtained from the savings are also given.

9.3 Application of the long-term forecasting of DSM on a baseline

For the long term forecasting of the impact of DSM in a region this normalized baseline was taken to perform the calculations on. Results of an actual energy audit of the Engineering Tower on the main campus that was performed by AZ Dalglish assisted by WH Kaiser, was used. The purpose of the project was to identify economic viable DSM measures. These measures would provide a benefit to the supplier of electricity and also be a profitable investment opportunity for Eskom.

The following paragraph gives a short overview of the specific building and the system. Secondly the measures considered are discussed. The impacts of these measures are then illustrated on the energy use of the campus.

9.3.1 Facility profile

A Description of the Building

The Engineering Tower is situated on the campus of the University of Pretoria. The building was built in 1973. It has a total of 16 levels. The total floor area is 7600m² of which 4120 m² is air-conditioned.

Levels 1 and 2 are used as lecture rooms and are below ground level. Most of these two floors are constructed as a double volume. There are a total of ten lecture rooms. The central air-conditioning plant and the transformer room is found on level 1.



Figure 9-1: Front view of the Engineering Tower

Levels 3, 4 and 5 are used as lobby areas. Levels 6 to 15 are used as offices. There are a total of 167 offices on these floors. Level 16 consist of two rooms on the roof of the building and is the service area of the four elevators in the building.

Spaces that are not used as lecture rooms or offices are used as tearooms, storing spaces, toilets, kitchens and waiting areas. The lecture rooms have seats for 715 students and about 150 people occupy the rest of the building. The typical building occupancy is 800 persons.

The offices are occupied from Monday to Friday throughout the year from 8:00 to 16:00. The lecture rooms are occupied on weekdays only during the University's semester. For 2000, the semesters for the university were as follows: 2 February to 24 March, 3 April to 27 June, 17 July to 22 September and 2 October to 6 December. Occupation starts at 8:30 and ends at 22:00.

A.1 Building systems

A central air-conditioning system is used to condition the air supplied to most of the building. About ten split units condition a small section of the building. All the spaces that are conditioned by split units are found behind the lifts.

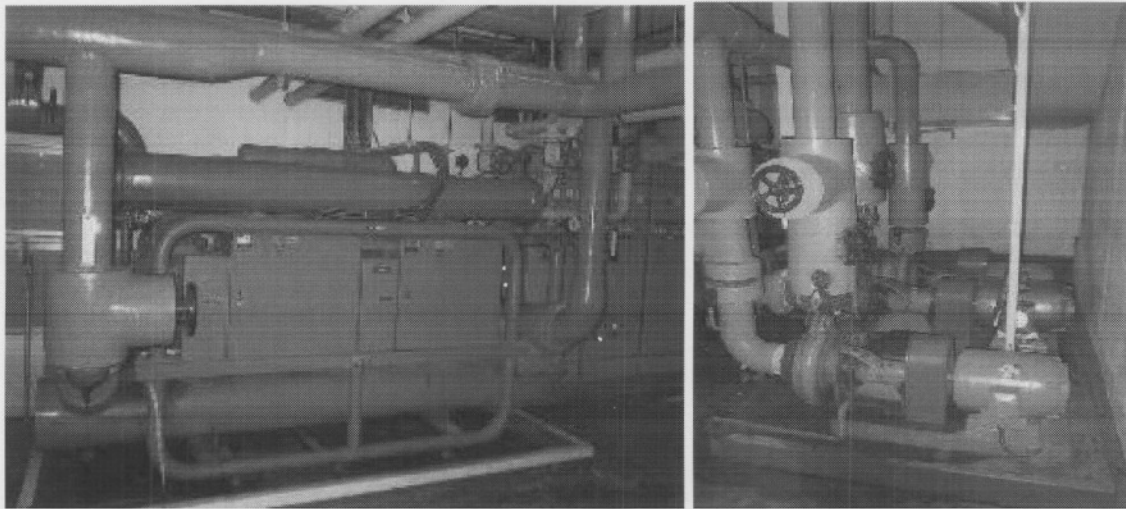


Figure 9-2 .The reciprocating chiller plant and condensing water pumps

Two reciprocating chillers with a total cooling capacity of 800kW are installed on level 1. The two chillers have two circuits each.

Chilled and condensing water pumps constantly pump chilled water to the respective air handling units (AHU). Three chilled water pumps are installed. One pump is used to pump chilled water to the fan coil units (FCU) in the offices and the AHU that serves some offices. This pump is rated at 30kW. The other two pumps are installed in parallel of which one is active and the other is on standby. These two pumps pump chilled water to the air-handling units (AHU) which serve the lecture rooms. They are rated at 15 kW and 1355 l/min each. The two condensing water pumps are each dedicated to a specific chiller. They are rated at 7.5 kW and 1110 l/min each. No standby condensing water pumps are installed.

The condensing water pumps pump the condensing water to the two open-loop cooling towers that are situated on the roof. Each cooling tower is dedicated to a specific chiller. Each cooling tower is equipped with two fans that are staged to control the water temperature returning to the chillers. The motor ratings of the two motors are 5.5kW each.

There is no central heating plant present in this building and also no central point in the building at which domestic hot water is heated. Water is heated with small geysers throughout the building.

External blinds are fitted in front of the building's windows that can manually shift to allow for at least 80% shading.

9.3.2 Building simulation

The aim of the computer simulations were to assist in performing parametric analyses of the building and its systems in order to assist in identifying electricity cost saving opportunities without reducing the indoor comfort conditions in the building. The parametric analysis of the building systems relied primarily on the VisualDOE a computer simulation programme that uses engineering equations. VisualDOE is a comprehensive building simulation program that is widely used internationally to perform hourly simulation of buildings and their systems of which the air-conditioning system is the most important.

The first step was to make sure that the simulation results of the building were correct. For this reason a verification process was performed where the simulated results were compared with actual measurements and information obtained from the monthly electricity bills. Once satisfied with the accuracy of the simulations a Base Year simulation was constructed. The Base Year simulation was used as the norm against which the electricity cost saving opportunities was evaluated.

The simulation model of the building and its systems were constructed in the VisualDOE simulation program. The information required as inputs were obtained from the conducted site surveys, operations and maintenance manuals, interviews with facility operations personnel, equipment manufacturers and on-site measurements.

The input given for the simulations ranged from the occupation schedules of the buildings to the construction of the building.

The building was verified with hourly measured data and annual energy accounts. The various DSM options were generated by changing the appropriate variables in the software.

9.3.3 DSM Options considered

A DSM option 1: Switching off unnecessary air-handling units during off peak hours.

What are the problems?

The measurements of the energy audit revealed that some of the air-handling units feeding the classrooms were running 24 hours a day, 7 days a week. For this measuring period the air handling units were never switched off.

Why are the problems experienced?

Motion detectors and temperature sensors that are installed in the classrooms control the air-handling units. This control system was not working.

The chillers were not in operation, due to the fact that a chilled water pump was overhauled. It is therefore a possibility that the fans were switched on to operate in this manner in order to use the ventilation system as cooling.

How can the problems be solved?

It is recommend that the control system be checked to see why it is not working and that it must be repaired. If it is decided that timers be installed, we recommend that the following start and stop times be programmed into the system for all the air handling units:

Weekdays:	Start:	6:00	Stop:	22:00
Saturdays:	Start:	6:00	Stop:	14:00
Sundays:		Off		



Chillers

Weekdays:	Start:	6:00	Stop:	20:00
Saturdays:	Start:	6:00	Stop:	14:00
Sundays:		Off		

B DSM option 2: Converting the constant air volume system to a variable air volume system and switching of the AHU and switching off the AHU

What are the problems?

The constant air volume (CAV) system currently installed is energy intensive units. Air is supplied at a constant volume to the classrooms. On colder than average days, the air supplied by the air-handling units needs to be reheated before entering the rooms. Thus resulting in high- electricity use and electricity costs. If a classroom is not fully occupied, the same amount of air is supplied as whom the classroom was fully occupied.

Why are the problems experienced?

CAV systems supply air at a constant volume to conditioned areas. The same amount of air is supplied even if little cooling is needed.

How can the problems be solved?

It is recommend that the CAV system be converted to a variable air volume system. Either dampers or variable speed drives need to be installed to regulate the supply airflow rates. As this option is not on economical viable on its own it was combined with DSM option 1.

9.3.4 Results

The results obtained from the analysis are shown graphically. Different graphs can be drawn evaluating the data for various time frames and indices. To illustrate some of the options that are available only a few graphs are shown. These are:

- Hourly impact on the total energy use of the campus for a single day.
- Monthly energy use and maximum demand for a single year.
- Cumulated annual energy use and the maximum demand of the year.
- Cumulated energy use off all the years
- Cumulated particles discharge

Finally the economic evaluations of the two DSM options are shown.

This information then can be used to determine which option is the most viable. This is determined by looking at the various indices economic indices. The impact of the specific hourly demand could be also being investigated.

9.3.5 Graphical results

A Comparison for a single day

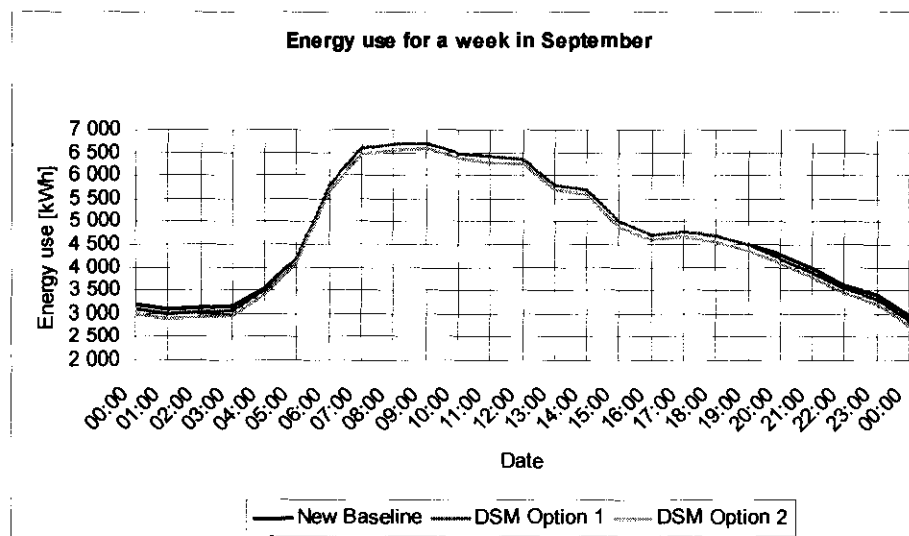


Figure 9-3: Comparison of the DSM options for a single day in August

Figure 9-3 illustrates that there is only a small difference between the new baseline and the DSM options. The DSM options included in this study are very small if compared to the total of the campus.

DSM option 1 reduces the energy use of the campus only after-hours, when the air-conditioning system of the building is switched off. The impact of this DSM option is very small and therefore only a small deviation could be detected. The DSM option has little to no impact on the national maximum demand, which occurs from 18:00 to 20:00.

DSM option 2 has a larger impact on the daily energy use. The option impact is larger impact, from approximately 19:00 to 5:00 in the morning. This option has only a small impact in the national maximum demand, which from 18:00 to 20:00. During office hours, the DSM option impact was approximately constant, but still relatively small.

Figure 9-3 could be extended to indicate any number of days for a year, to illustrate for example the various effects over the seasons. For DSM option 1 and 2 this does not change significantly enough.

B Monthly comparison

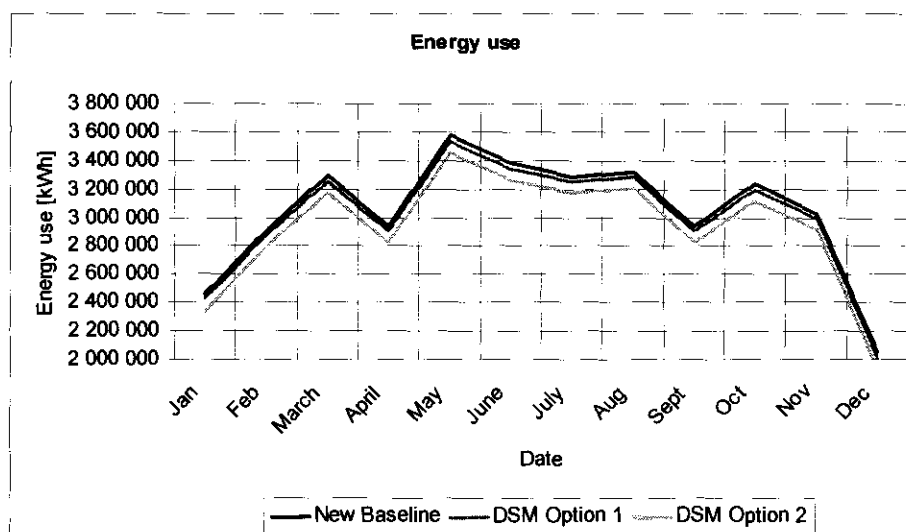


Figure 9-4: Monthly comparison of the DSM options for January to December

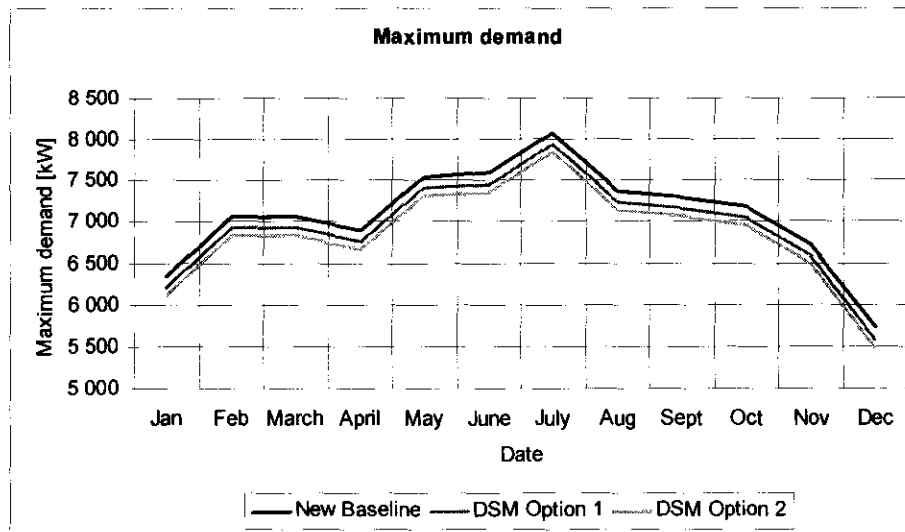


Figure 9-5: Monthly maximum demand comparison of the various DSM options for January to December

Figure 9-4 illustrates the integrated energy use of the campus for the various months. The graph illustrates that DSM option 1 lays virtually on top the new baseline. DSM option 2 has a larger influence on the monthly energy use of campus. It seems that the impact of the two DSM options is less over the holidays, especially during January and December. The impact if the DSM options are not that large during the winter holidays, due to extra classes and winter school. Furthermore, in the winter there are more support personnel and lecturers that occupy the building.

Figure 9-5 illustrates that DSM option 2 has a larger impact on the maximum demand of the campus. The campus is billed according to a two-part tariff structure, therefore the maximum demand can occur during any time of the day. Thus, even though the DSM option has no influence on the national maximum demand, it has a definite influence on the maximum demand of the campus.

It seems that the values of the DSM options are more parallel with the maximum demand. This indicates that during the holidays the air-conditioning system's impact was very low, and the changes thus had a small impact.

B.1 Annual comparison

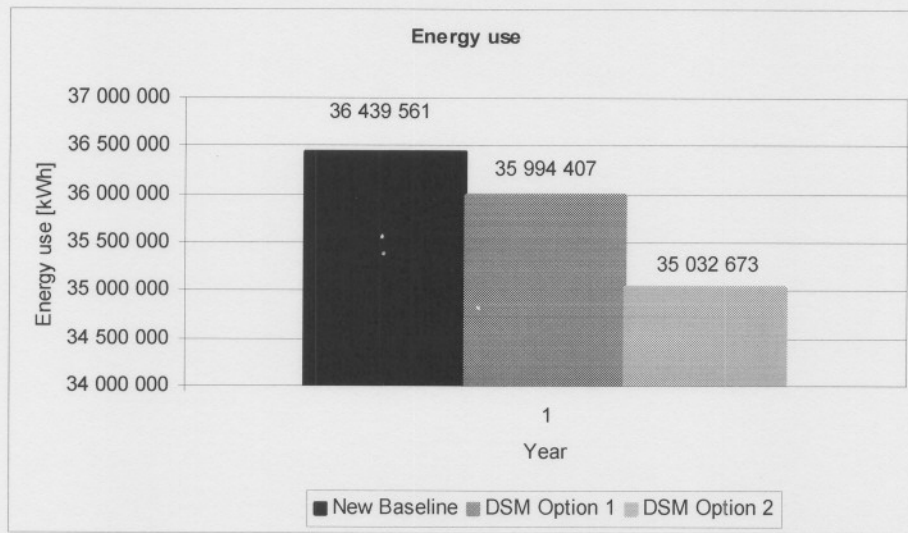


Figure 9-6: Annual energy use comparison of the various DSM options

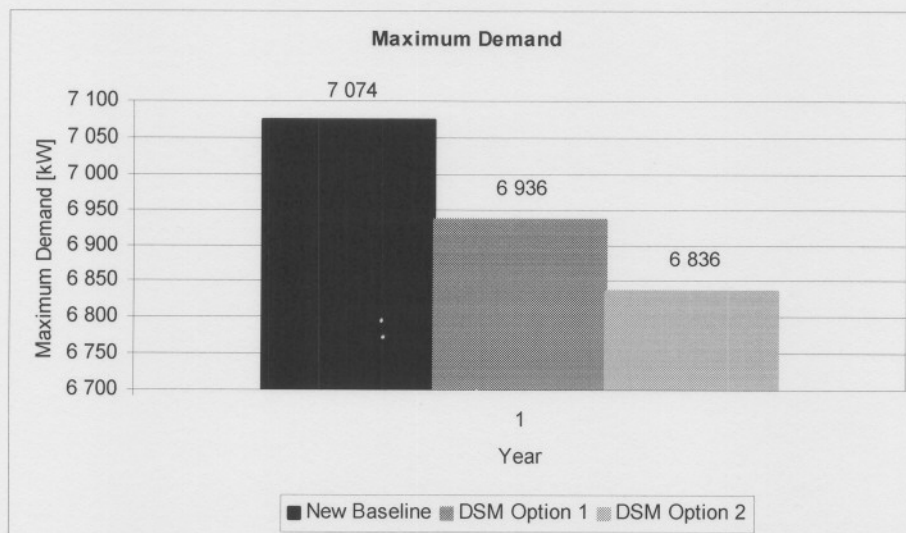


Figure 9-7: Annual comparison of the maximum demand for the various DSM options

Figure 9-6 illustrates the cumulative total annual energy use. The effect on the buildings is still small, but because the annual totals energy use is shown, the impact is more clearly illustrated. The graph indicates that the DSM option 1 results in a smaller annual saving. A DSM option 2 has a larger annual saving of approximately 1400 MWh per annum. From an energy use point of view it thus seems that DSM option 2 is the better choice.

Figure 9-7 illustrates the average maximum demand that was recorded during the year. The graph clearly shows that DSM option 2 has the largest reduction in the annual maximum demand with an average reduction of 240 KW.

B.2 Ten year comparison

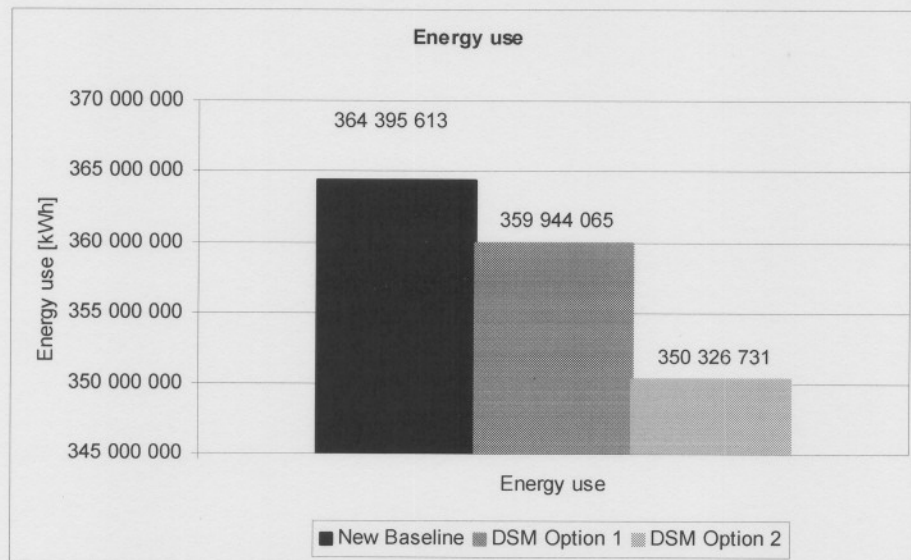


Figure 9-8: Total energy use comparison of the various DSM options

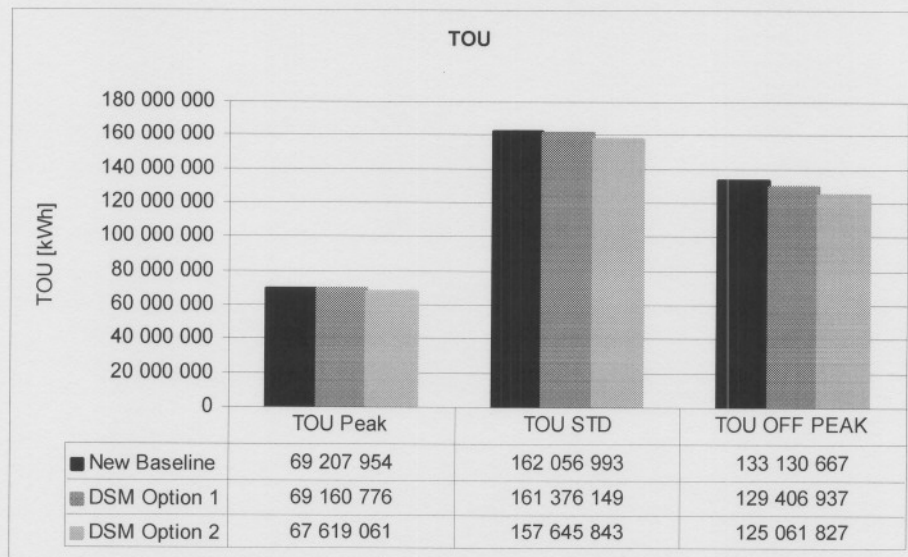


Figure 9-9: Total energy use comparison of the various DSM options for the time of use tariff structure

Figure 9-9 illustrates the effect the DSM options will have on the various time periods of the Time Of Use (TOU) tariff structure. For Eskom it is of utmost importance to reduce the energy use for the maximum demand periods, because of overall high-energy use during these periods.

The graphs illustrates that the DSM options had a small impact on the time of use tariff structure peak billing period. The largest impact of the options is for the off peak period. Depending the importance for Eskom of reduction of the energy use during the peak hours. This might be a drawback in the implementation of the DSM options.

The graph indicates that the DSM options had a small impact on the TOU tariff structure during the peak period. The largest impact of the options is for the off-peak period. The above mentioned observations might be a drawback in the implementation of the DSM options, as Eskom is more interested in savings during peak hours.

DSM option 2 had the largest impact on the different time periods investigated of the TOU tariff structure.

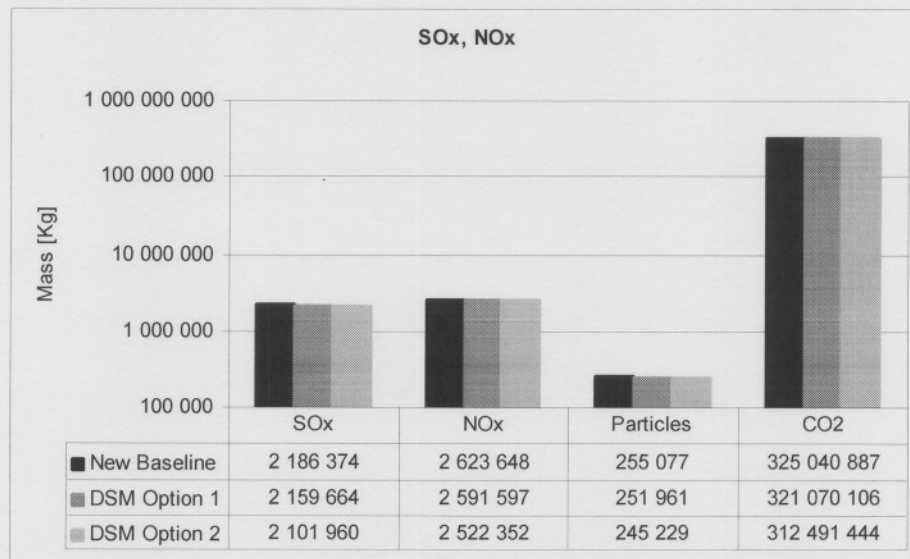


Figure 9-10: Comparison of various harmful gases for the DSM options

Figure 9-10 illustrates the effect of the DSM options on harmful gasses that are polluting the environment. It is observed that the DSM options have a small impact, due to small effect of options proposed. The graphs illustrates that DSM option 2 has the largest impact for the cases investigated.

C Financial results

The table below indicates forecasted saving and financial impact of the various DSM options investigated, for a ten-year economic life cycle.

Table 9-1: Financial analysis for the DSM options

Description	DSM Option 1	DSM Option 2
Annual Energy cost of base year	R 7 803 508	R 7 803 508
Annual savings of this option	R 124 747	R 281 287
Electric inflation rate	5%	5%
Initial cost	R 30 000	R 340 000
Discount rate	15%	15%
Net present value	R 715 193	R 1 340 300
Internal rate if return	421%	87%
Percentage of total energy cost saved	2%	4%
Straight payback period (Years)	0.2	1.2

From the information given it can seen that both the DSM options provide for a straight payback period of less than three year, which is generally acceptble in the energy industry.

The DSM options display a very high net present value. This is because this value is calculated using the annual energy cost, which is very high. The percentage of the energy cost saved is so low, because of the relative high-energy cost of the campus. This percentage increases dramatically if the annual energy cost of the Engineering tower is rather used.

These indicators are only guidelines in determining which of the DSM option would be of greater importance to the client, and which DM option has to be chosen.

The information investigated strongly suggests that DSM option 2 is a better choice, from an economical, environmental and energy use point of view. A choice between these options has to be made depending on how much the investor wants to spend.

9.4 Conclusion

The methodology to forecast the hourly long-term impact of DSM in region was illustrated by a case study. The results indicated that the effect of the different DSM options could be seen on the baseline.

The graphs shown, illustrated the impact from an hourly point view, to a monthly, an annual and a ten-year period. Finally a financial analysis was also shown.

The different graphs could then be used to determine the impact of the DSM options for the various periods investigated. The greatest advantage of this technique is that the hourly impact of a specific DSM option could be seen. This was illustrated by looking at the hourly energy use for a single day and the TOU impact for the ten-year period. This is of great importance to Eskom, because Eskom needs to decrease the peak periods energy use. From Eskom perspective, the two DSM options investigated, have a to small impact on the maximum demand to continue this project.

This information could then be used to determine which DSM option was the best for the specific situation. It is important to remember that this tool does not include the effect of market penetration etc. These factors could have an influence on the projected savings the different DSM options will actually have.



10.1 Introduction

In this chapter a summary is provided of the most important results that were discussed in the previous chapters. From these results conclusions will be made, leading to recommendations for further research.

10.2 Conclusion

From the study undertaken it can be concluded that:

1. The technique of using NN's to model the baseline using the whole year's data gave sufficient accurate results using the LNSPC set of criteria. The results indicate that this baseline adheres to the set of criteria set, and thus can be used to forecast the long-term impact of DSM for a region.
2. The major problem experienced with the technique was that hourly data for the whole year is needed to model the energy use accurately. Subsequently a study was conducted to reduce the input variables needed for the training of the NN.
3. The investigation revealed that the minimum amount of data a NN needs, has to have at least a set of all the combinations that contains elements of all the major factors that have an influence on the energy use.
These points have to include the turning points in the seasonal weather pattern, also during national and regional holidays. For the case study, the minimum data needed to successfully model the energy could not be reduced, due to the encoding of the months. This confirms that NN cannot extrapolate values for data of which it is unfamiliar with.
4. The use of a NN is a viable technique for Eskom to model the energy use for a region such as a university campus, with wide diversity in energy use. This use of a NN for modelling a baseline indicate that it can be extended to a higher level of distribution where there is a higher diversity of energy use for example cities and even to a region like the Gauteng province.
5. The traditional techniques described in this investigation are very labour and resource intensive. On the other hand the use of NN's for modelling an hourly model gives an hourly indication of a simulated energy use.

Furthermore this technique is simpler, faster and more accurate than traditional detail modelling techniques with timesaving of up to 90 %.

6. This baseline could then be used to forecast the long-term impact of DSM for the case study. Various indices were used to illustrate this. These indices then could assist the various stakeholders in deciding if DSM is a viable option.

This study delivered a computer application that could be used to:

1. Determine the hourly as well as the monthly and annual impact of an investigated DSM option. The advantage of this technique is that the DSM options could be evaluated for a specific hour of the day, to determine, for example, the impact of the daily peak demand.
2. Evaluate the various DSM options on a monthly and on annual basis as well as for a ten-year period. Various indices could be used, ranging from the amount of saved energy to the reduction in NO_x and SO_x emissions. The DSM options could further also be evaluated using various economic indicators such as the internal rate of return and the straight payback period.
3. Demonstrate the commercial benefits and energy savings by the application of DSM strategies and procedures, to building owners and tenants, architects and engineers.

The demonstrations of the financial benefits of applying DSM could encourage property stakeholders to accept DSM and apply it as part of planning and construction as well as the operation of a building. This could then have the following impacts:

- The minimising the fluctuations in demand that Eskom is currently experiencing.
- The delaying the estimated peaking shortage predicted for South Africa.
- Decreasing the energy usage per GDP for South Africa, and making it more competitive in the world market.

It can be concluded that the secondary effect of the project will initially be minimal, but as DSM grows, a major effect can be expected on the economy of South Africa.

10.3 Recommendations for further study.

The following recommendations for further work are made:

1. Currently the methodology of using NN's to construct a baseline was only tested for a single case study. This has to be extended for different applications, for example, a commercial park, industrial park, residential area and combination of these, to test how well it performs in these cases.
2. The current technique relied in the encoding of the month to establish the baseline. This has a huge disadvantage that a whole year of data is needed to train the model. Alternative ways that will have accurate enough results need to be investigated. For example dividing the year up into six blocks of data, grouping months together with approximately the same weather conditions, might be a solution.
3. This technique was only tested on a relatively small case study, with relatively medium diversity. It is recommended that a study has to be undertaken to establish which point of higher distribution this technique could still apply.
4. An investigation could also be launched to determine the minimum number of buildings with varying diversity, for which this technique successfully be could used for.
5. An important part of the long-term forecasting of DSM in a region is to monitor and verify the forecasted savings for that area. A methodology has to be established to determine the true impact of the DSM options and procedures that were implemented.