

# Developing load models for Eskom residential customers

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## PREFACE

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## **ABSTRACT**

**TITLE:** Developing Load Models for Eskom Residential Customers

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In 2008, South Africa faced a severe electricity shortage which manifested in load shedding. This resulted in numerous initiatives for demand side management and energy efficiency being implemented by Eskom. In addition, it was equally important to understand the dynamics of the load, and the behaviour of customers to these initiatives and to the situation in all sectors.

Understanding the load and the behaviour of the customers was achieved through gathering data (electricity consumption and socio-demographics), analysing this data through proven techniques, and then providing models that would assist in decision-making.

The objective of this dissertation is to provide developed load models in the residential sector. The outcome will enhance network planning, load forecasting, tariff and rates design, improved demand management and tackle theft issue from an informed view point.

The methodology followed was to identify and define the problem, conduct the literature review to avoid duplication of research work and also to obtain best practices internationally. Subsequently, a sample design was conducted and sites for logger installation were identified. The installation of data loggers at the customer's service point (household) in various sites, data remote downloading and storing, validation and analysis of data were done in consultation with all stakeholders through working groups, steering committees and investment committees.

From the data gathered it was established that in an area such as Matshana, the average gross income is about R2 600 per household per month, there is approximately 39% hotplate ownership, and 79% ownership of fridge or fridge-freezer with an estimated consumption of 465 kWh per household per month. The after diversity maximum demand for Matshana is 1.54 kVA.

The average gross income for Mcubakazi is R7 100 per household per month, there is approximately 47% hotplate ownership, and 86% ownership of fridge-freezer with an estimated consumption of 330.4 kWh per household per month. The after diversity maximum demand for Mcubakazi is 1.38 kVA. This is useful information for the purpose of low-voltage network design and planning.

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## LIST OF ABBREVIATIONS

ADMD	After Diversity Maximum Demand
CT	Current Transformer
DLR	Domestic Load Research
DSM	Demand Side Management
ECO	Energy Conservation and Commercialization Project
GDP	Gross Domestic Product
GMM	Gaussian Mixture Model
IT	Information Technology
LPI	Load Profile Index
LSDS	Load Studies Data Store
LVF	Low-voltage Feeders (nominal voltage levels up to and including 1 kV)
MV90	Multi-vendor system
PDF	Probabilistic Distribution Function
QoS	Quality of Supply
UK	United Kingdom
USA	United States of America

## UNITS

A	Current
kVA	Kilovolt-ampere
kW	Kilowatt
kWh	Kilowatt-hour
LF	Load Factor
P (W)	Power
Q (Vars)	Reactive Power
R ( $\Omega$ )	Resistance
Z ( $\Omega$ )	Impedance

# CHAPTER 1: INTRODUCTION

## 1.1 BACKGROUND

In 2008, South Africa faced a severe electricity shortage which manifested in load shedding. This resulted in numerous initiatives for demand side management (DSM) and energy efficiency being implemented. In addition, it was equally important to understand the dynamics of the load, and the behaviour of customers to these initiatives and to the situation in 2008 and the future in all sectors. The focus of this dissertation is mainly on the domestic sector.

The effective and economic capital expansion of the electric power delivery system requires well-prepared and structured medium- to long-term load forecasts that provide a confident prediction of future loads. The network planner has to anticipate how much power must be delivered as well as where and when it will be needed. Significant work has been done to establish a load forecasting tool that will assist Eskom distribution network planning to predict and consolidate load forecasts in a single data repository.

This will enable distribution network planning to provide consolidated regional and national views of predicted future loads. The established load forecasting tool requires load profile data that will be used to calculate coincidence factors between loads of different classes and sub-classes over a 24-hour day for different seasons of the year. This requires an understanding of the load behaviour in a typical weekday, Saturday or Sunday for both winter and summer seasons.

At present, focus has been on understanding domestic load behaviour. This has produced domestic load profiles that can be used in the distribution planning environment in predicting profiles of the different sub-classes within the domestic consumer group. Providing these profiles will go a long way in assisting network planners to better understand load behaviour and refine future load prediction, which will ultimately produce effective and economic capital expansion plans.

Understanding the load and the behaviour of customers was achieved through gathering data (load and socio-demographics), analysing data using proven techniques, and then providing models that will assist in decision-making.

## **1.2 RESEARCH NEED**

The design of low-voltage distribution systems requires a different approach than the design of transmission systems. This is partly due to the lack of measuring systems and data acquisition [1].

Since the early 1990s, historically the targeted areas for electrification have been rural and township areas. These areas posed a challenge because of the uncertainty regarding electricity consumption. Therefore, it becomes a significant requirement to comply with the loading capacity of equipment and also to provide the desired voltage to the customer. Hence, there is a research need and importance to predict, model and forecast the residential load.

Although this might sound easy to perform, the difficulty is to model customer demand in an environment where there is no proper infrastructure such as profile metering. This is because customers' usage of appliances is not known and depends on various factors such as (more factors will be discussed later in the dissertation):

- Household income
- Size of the house
- Temperature (weather conditions)

As stated by Dickert and Schegner [1], the main economic criteria are capital and operating cost (including technical and non-technical losses). It is possible to find a feasible design within these criteria. However, not knowing the future load and technology changes make finding the best design with the lowest costs impossible.

It is for this reason that electricity utility companies in South Africa, through platforms such as the National Rationalized User Specification Working Group [2], sought to standardise the network planning guidelines and procedures.

The recent target achievement of 90% electrification in residential areas has a potential to shift the focus from new electrification networks to existing network expansion, refurbishment and optimisation. This can be best achieved through estimation of after diversity maximum demand (ADMD).

### **INFORMATION REGARDING ADMD**

ADMD is the basic electrical load, on a per customer basis, used to design an electrical network. It represents the maximum demand calculated for a distribution substation with more than 60 customers in total connected to that substation. Where there are fewer than 60 customers, diversity is used to estimate maximum demand [3].

The design ADMD values are based on the measured ADMD values with an allowance made for potential growth over the life of the cable asset. This allowance reflects the range of climatic zones, socio-economic and expansion potential factors applicable in each town and can be influenced by, but not limited to [3]:

- Propensity for growth in residential housing
- Increasing affordability to use air-conditioning and other electric appliances
- Change in the socio-economic demographics in regional areas

The ADMD values play a critical role in ensuring that the design and planning of distribution networks are done cost effectively and also with a low load forecasting error margin.

In addition to planned expansion, increased application of electric equipment will generate an increase in load. When sizing components such as transformers or feeders for the area system, consider possible load growth in addition to that included when determining individual loads [4].

The advantage of using ADMD is the ability to design and plan distribution network systems that are capable of supplying reliable electricity for longer periods without reinforcement.

### **1.3 PROBLEM STATEMENT**

Access to electricity can be a powerful economic and social stimulus in a developing country. Therefore, there is a significant political and social demand to construct new distribution feeders to make supply available [5].

The problem encountered that necessitated this research work is to design and plan the distribution network in a cost-effective manner as overdesigning or underdesigning has a cost attached to it.

Developing countries such as South Africa aspire to achieve the goal of making electricity accessible to all. Although a significant percentage of 90% electrified has recently been achieved, there are some problems in expanding the network, refurbishing and maintaining the existing network. In fact, power demand (kW) is more complicated to predict than energy demand (kWh) because of its random nature and its acute fluctuating aspect [6].

This is because power demand occurs in a short period with high or peak demand whereas energy demand occurs over a longer period. Example is where household 1 and household 2 both consume the same total energy of 100 kWh per household, but household 1 consumes 10 kW in 10 hours whereas household 2 consumes 100 kW in 1 hour. The utility has to ensure availability of capacity during that peak period for household 2 and there is an infrastructure cost implication to be incurred by the utility.

Hence the problem statement:

Decision makers in network planning and load forecasting are faced with a complex environment in the residential sector to execute their tasks to ensure reliable and sustainable electricity to customers.

This research process seeks to unlock and avail potential solutions by answering the research questions.

## **1.4 RESEARCH QUESTIONS**

The research questions are:

- What socio-demographics parameters (such as income, appliances, employment and floor space) do the levels of demand, consumption and load profile shape relate most to?
- What peak demands, consumption and shape of the load can be expected from the different types of community?
- How big is the influence of external factors on the levels of demand, consumption and load profile shape?
- What are the international trends and lessons learnt?

It was the aspirations of this research to adequately answer the research questions that seek to address the problem statement. By answering these research questions, the objectives would then be achieved.

## **1.5 OBJECTIVES**

The objectives identified are:

- To gain better understanding of the distribution network performance and develop load models that will assist in network design and planning
- To use proven and new techniques in load forecasting

The main objective is to enhance the decision process on the infrastructure investment based on informed and tested solutions.

## **1.6 OVERVIEW OF DISSERTATION**

This section provides the overview of the dissertation.

## **CHAPTER 1: INTRODUCTION**

This chapter presents background that forms the basis for this research work. The problem and need for this research, and the applied approach in resolving the problem are also presented. This is achieved by answering the posed research questions.

## **CHAPTER 2: ELECTRICAL LOAD INFORMATION**

The dissertation further continues to present the electrical load information and the factors affecting the load. The different types of residential load are briefly considered with reference to economic, social and technical effects on the loads.

## **CHAPTER 3: VARIOUS ELECTRICAL LOAD MODELS**

The measurement of data provides a huge opportunity in developing load models. This chapter therefore presents the various load models that were evaluated and used during the research processes. Both internationally and nationally, many researchers in load modelling considered the Gaussian probabilistic distribution function to better model the networks.

## **CHAPTER 4: DATA ACQUISITION OF ELECTRICAL LOAD**

Data plays a critical role to achieve the set objectives. This chapter presents types of data acquired, namely, socio-demographic and meter datasets and the technology used. It then presents the architectural infrastructure for data storage.

## **CHAPTER 5: RESULTS**

This chapter presents data analysis and the results obtained from two sites, namely, Mcubakazi and Matshana. Both these sites have lower income group consumers where development is taking place. Hence, the probabilistic model was used for load modelling.

The residential profiles are also presented in this chapter for the two sites showing the morning and evening peaks. These profiles also depict the weekday and weekend profiles.

## **CHAPTER 6: CONCLUSIONS AND RECOMMENDATIONS**

Lastly, the conclusions and recommendations are presented. It is concluded that electrical load modelling is required globally; however, from the identified models and the results achieved, one is able to realise that conditions and situations differ from country to country, region to region, and one cluster of customers to another.

It is recommended that the Gaussian probabilistic distribution function for probabilistic modelling be further enhanced as the residential sector is dynamic, particularly in developing countries such as South Africa.

## CHAPTER 2: ELECTRICAL LOAD INFORMATION

### 2.1 PREAMBLE

This chapter provides a clear description of a load and all considerable factors. By having a clear knowledge and understanding of the requirements, one is able to acquire the appropriate information from the vast information at one's disposal. This information was critical and necessary for the modelling process during this research.

### 2.2 DEFINITION OF LOAD

A clear load definition is crucial to avoid any ambiguity in providing technological and mathematical solutions to address the identified problems. The electrical load is defined as [7]:

*“The electrical energy that is consumed by a component, circuit, device, piece of equipment, or system that is connected to a source of electric power, in order to perform its functions.”*

External (weather) and internal driving forces (habits) influence the use of appliances. Individual consumers may respond differently to these forces, but a definite trend is visible when a large number (>30) of consumers is investigated. A load profile is a graphical representation of trends in appliance use. Periods with similar trends are grouped together to form typical load profiles [8].

In a three-phase power system, the relation between active power (P), load current (A), and load factor (LF)  $\cos \phi$  is defined as:

$$P = \sqrt{3} VI \cos \phi$$

Most loads will draw more active and reactive power if the supply voltage is increased. The possible increased consumption must be considered in light of the types of load being supplied.

The voltage magnitude affects the time for which thermostatically controlled heating devices draw load and thereby affects the load coincidence. The applicability of load recordings to other networks needs to be considered if the voltage variations in these “other” networks are significantly different to those of the network/customers upon which the load data is based [9].

Residential distribution planning and design essentially consist of placing and sizing electrical equipment to satisfy predicted consumer loads. For low-voltage feeders (LVFs), voltage drop is the predominant constraint in sizing. Owing to the stochastic<sup>1</sup> nature of domestic loads, a statistical description of the loads is required [2].

## 2.3 CLASSIFICATION OF RESIDENTIAL LOADS

Residential appliances can be classified in several ways. Most equipment can be assigned to brown goods, white goods, small appliances or lighting [1].

### **BROWN GOODS**

Relatively light electronic consumer goods are often called brown goods. They can be divided into equipment for communication or entertainment:

- Communication equipment: personal computer, LCD<sup>2</sup>, printer, scanner, phone, router, etc.
- Entertainment electronics: television, CD/DVD<sup>3</sup> player, hi-fi system, video game, etc.

### **WHITE GOODS**

White goods are also called major appliances or whiteware. These are major domestic appliances accomplishing some routine housekeeping tasks such as cooking, food preservation or cleaning.

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<sup>1</sup> Random variation with respect to time

<sup>2</sup> Liquid crystal display

<sup>3</sup> Compact disc/digital versatile disc

- Kitchen appliances: stove, refrigerator, freezer, dishwasher, microwave, etc.
- Laundry appliances: washing machine, laundry dryer, etc.
- Heating, ventilation and air-conditioning: air conditioner, water heater, etc.

### **SMALL APPLIANCES**

In comparison to brown and white goods, small appliances are portable or semi-portable. Many small appliances are kitchen appliances or devices for personal care. Examples are:

- Kitchen appliances: kettle, toaster, blender, etc.
- Household appliances: fan, iron, sewing machine, vacuum cleaner, etc.
- Electronic devices: mobile phone, digital camera, radio, etc.
- Personal care: hairdryer, curling iron, shaver, electric tooth brush, etc.

### **LIGHTING**

The illumination of homes during the night is also an important part of residential energy consumption. However, due to energy saving lamps, the effect of lighting on power system planning is decreasing.

## **2.4 FACTORS INFLUENCING THE ELECTRICAL LOAD**

If the electric load consists of a large number of consumers ( $n$ ), then the total load may be regarded as ( $n$ ) times the mean value of ADMD. This is due to the phenomenon known as central tendency [2].

However, as the number of consumers forming the load decreases ( $n'$ ), so the uncertainty of the size of a combined load increases and allowance should be made for the probability that the load will exceed  $n'$  times the mean value. Table 2-1 presents some of the socio-demographics characteristics that affect the ADMD.

There is no unique model that can be applied for utility companies [10], it is imperative for utilities to consider factors influencing the load.

Table 2-1: Socio-demographics characteristics affecting ADMD [2]

Characteristics	Effect on design load
Economic class of present and future residents	This will determine the appliances present in a household
Social characteristics such as number of persons or households on each stand	The estimated future usage patterns of appliances that contribute significantly to a consumer's load at times of peak demand, such as a hotplate/stove, space heating, water heating, washing machine, tumble dryer and air conditioner, can increase the ADMD selected
Community habits (shift work, etc.)	If a large percentage of a residential area's population works fixed hours (such as shift work at a mine or factory), the parameters of the load model might have to be changed
Load control methods ("ripple control", load limit switches or circuit breaker tariffs)	Take cognisance of the influence of "ripple control" on electric water heaters, where this is to be applied, and reduce the ADMD accordingly
Cost, ease of use, availability of and social preference for alternative energy sources	The estimated continued usage of alternative energy in the future as a substitute for major energy appliances, such as using coal stoves instead of electric stoves or hotplates, can reduce the ADMD chosen

A model for peak-load demand should consider these factors or part of them, depending on the country in which this model is going to be implemented. These factors are:

- The gross domestic product (GDP)
- The population
- The GDP per capita
- The multiplication of electricity consumption by population
- The power system losses
- The load factor
- The cost of one kilowatt-hour

The first four factors depend on the behaviour of the public, thus they may vary from country to country, whereas the last three factors depend on the electric power system and the load itself, as well as the consumption of power generated [10].

In addition to the factors listed above, Table 2-2 provides factors influencing the customer's load.

Table 2-2: *Additional factors influencing the residential load*

Item no.	Factors	Discussion
1	Customer	Residential: the penetration and usage of appliances as well as behaviour of customers.
2	Time	Load varies with time: day time, week or weekend, and also seasonal.
3	Climate	Ambient temperature, wind speed and radiation of the sun influence the customer to use heating or cooling equipment.
4	Other electric loads	Stove during cooking influences a kettle for water heating and also a fridge as a door is frequently opened.
5	Previous load values	Knowledge and availability of previous data play a key role in predicting future loads.

Geobased load forecasting attempts to combine available load information from, for example, a billing system with the geographical data that will influence the way in which the load will develop [11]. An example of load development over time is presented in Figure 2-1.

In view of this urban development, which is influenced by migration from rural to urban areas, electrical load modelling becomes critical for the purpose of network design and planning.

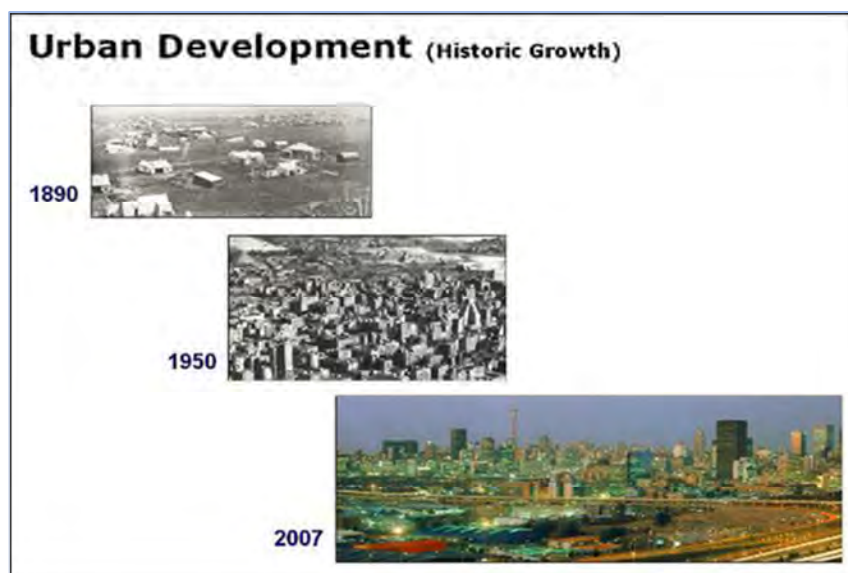


Figure 2-1: Pictorial timeline of urban development [11]

## 2.5 LOAD RESEARCH AND MODELLING IN OTHER COUNTRIES

Load research is performed globally by electricity utilities, academic institutions and other relevant organisations. Electrical load modelling and load research tend to be intertwined by researchers. This section discusses load modelling in various countries.

### UNITED STATES OF AMERICA (USA)

In the USA, load research is formally defined as: “An activity embracing the measurement and study of the characteristics of electrical loads to provide a thorough and reliable knowledge of trends in, the general behaviour of, the load characteristics of the more important electrical services rendered by the electric utility industry” [12].

Some utilities have been performing load research since the 1930s. The Association of Edison Illuminating Company Load Research Committee held its first organisational meeting in 1944. In 1978, the Public Utility Regulatory Policies Act required the utility industry to develop the load research programmes [12].

The Load Research White Paper [12] discusses the methodology named “regression method” to create a model to represent the customer’s load shape on an event day. Some of the models discussed are:

- Peak period energy model: If interval metering is unavailable, a model can be specified that uses peak period energy as a function of cooling degrees. Hourly kW is derived by applying an average hot day load shape to the resultant. The specified energy model may be of the form:

$$\text{kWh} = \beta_0 + \beta_1 \times \text{Cooling degree days}$$

- Hourly demand model: When interval metering is available, a demand model can be specified. One form of the model uses hourly demand as a function of cooling degree hours:

$$\text{kW} = \beta_0 + \beta_1 \times \text{Cooling degree days}$$

Temperature plays a critical role in modelling the load in the USA as shown in both energy and demand models.

## **AUSTRALIA**

Voltage quality is an important factor in the LVFs supplying residential customers. Traditionally the voltage drop along the feeder and specifically at the end nodes of a feeder is considered as one of the main voltage quality problems in the network peak hours [13].

Due to the significant and rapid increase in the penetration level of rooftop photovoltaic cells that are installed at households, several new voltage quality problems such as voltage rise, voltage unbalance and rapid voltage fluctuations are imposed to the LVFs.

## **FINLAND**

Finnish electric utilities use various applications in network planning, tariff planning and production planning that use the load models from the national load research project.

The Finnish load research project started in 1983 [14]. In 1996, there were more than 1 000 customers. The time interval in the Finnish load research project is 60 minutes.

The linking of load models to customer and network data is a critical phase before most of the calculations can be run [14].

The simple load model used in electricity distribution application of most Finnish electric utilities represents the customer's average hourly load  $P(t)$  and standard deviation  $s_p(t)$  as a linear function of the annual energy consumption  $W_a$  presented as follows:

$$\begin{cases} P(t) = L_c(m(t), d(t), h(t)) \cdot W_a \\ s_p(t) = S_{Lc}(m(t), d(t), h(t)) \cdot W_a \end{cases}$$

Where:

$m(t)$  Classifying functions resulting in a category where a specific hour  $t$  belongs. The value of  $m(t)$  is season, time of year, usually month, but may be a week

$d(t)$  The value of  $d(t)$  is a day type, usually day of week or working day/holiday

$h(t)$  The value of  $h(t)$  is hour (1 to 24) hours

$$\begin{cases} L_c(m, d, h) = E \left[ \frac{Wc(m, d, h)}{Wc, a} \right] \\ S_{Lc}(m, d, h) = \sigma \left[ \frac{Wc(m, d, h)}{Wc, a} \right] \end{cases}$$

The parameter  $L_c$  and  $S_{Lc}$  are estimated from load research data from the average and standard deviation of the hourly load recordings divided by the customer's annual energy consumption.

## UNITED KINGDOM (UK)

Following the significant development in business regulations, technology evolutions and various government policies towards low carbon generation technology, the main challenges before distribution companies are to improve their operating efficiencies, develop new tariffs, and offer new services to low-voltage consumers without significant capital burden [15].

This necessitated sample customer load profiles and the application of modelling techniques. The most common technique to model loads is through Gaussian distribution; however, the single Gaussian assumption is not justified for all the loads [15].

The UK generic distribution network project identified the following four types of consumer for developing generic load profile index (LPI) [15] as follows:

- Domestic-unrestricted
- Domestic-economy
- Industrial
- Commercial

The real and reactive power load profiles at the  $i^{th}$  bus were computed as follows:

$$P_i(t) = \sum_{j=1}^{N_c} \frac{P_{i,max}^j}{\max_{\tau}(P_{PI}^j(\tau))} P_{PI}^j(t)$$

$$Q_i(t) = \sum_{j=1}^{N_c} \frac{P_{i,max}^j}{\max_{\tau}(P_{PI}^j(\tau))} P_{PI}^j(t) \tan(\Phi^j)$$

Where:

$t, \tau$                       Half-hourly time instances of the year

$P_i(t), Q_i(t)$         Real and reactive power loads at the  $i^{th}$  bus at time instant  $t$

$P_{PI}^j(t)$	LPI value of the $j^{th}$ class of consumer at time instant $t$
$P_{i,max}^j$	Annual maximum demand of the $j^{th}$ class of consumer at bus $i$
$\phi^j$	Angle of average power factor of the $j^{th}$ class of consumer
$N_c$	Number of consumer classes

Figure 2-2 shows the probability distribution of load at four different buses with the profile of demand and density.

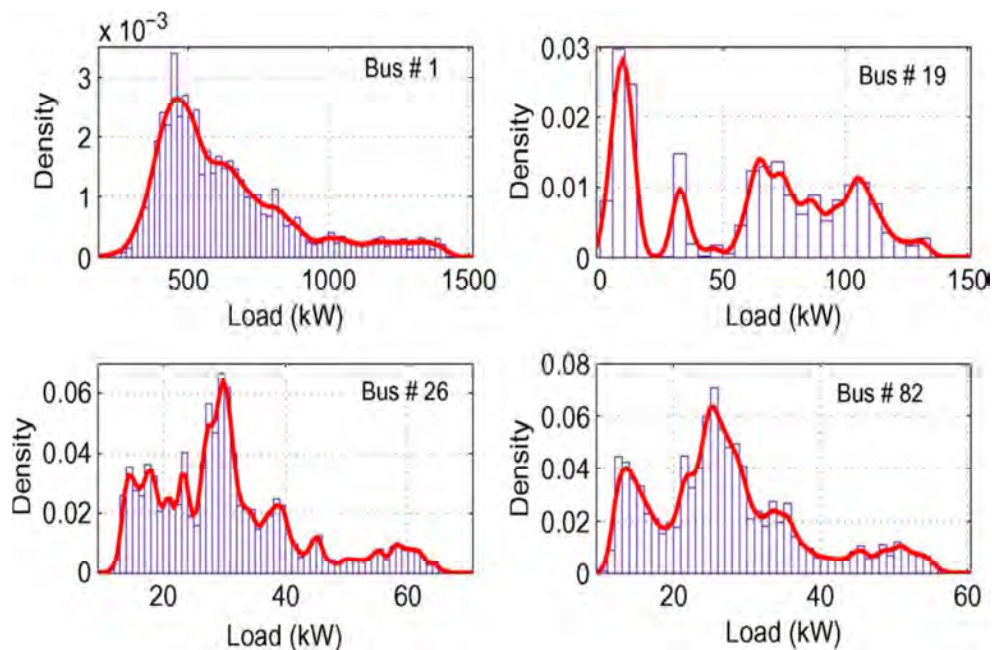


Figure 2-2: Probability distribution of load at different buses [15]

The typical power factors for all four classes of consumers were taken as 0.95, 0.99, 0.98, and 0.90 lagging, respectively.

The Gaussian Mixture Model (GMM) probabilistic distribution function (PDF) is a weighted finite sum of Gaussian PDFs as shown Figure 2-3. It is characterised by the number of mixture components, weights, mean and variance of each component [15].

The dotted lines in Figure 2-3 represent individual mixture components and the solid line represents the resultant density.

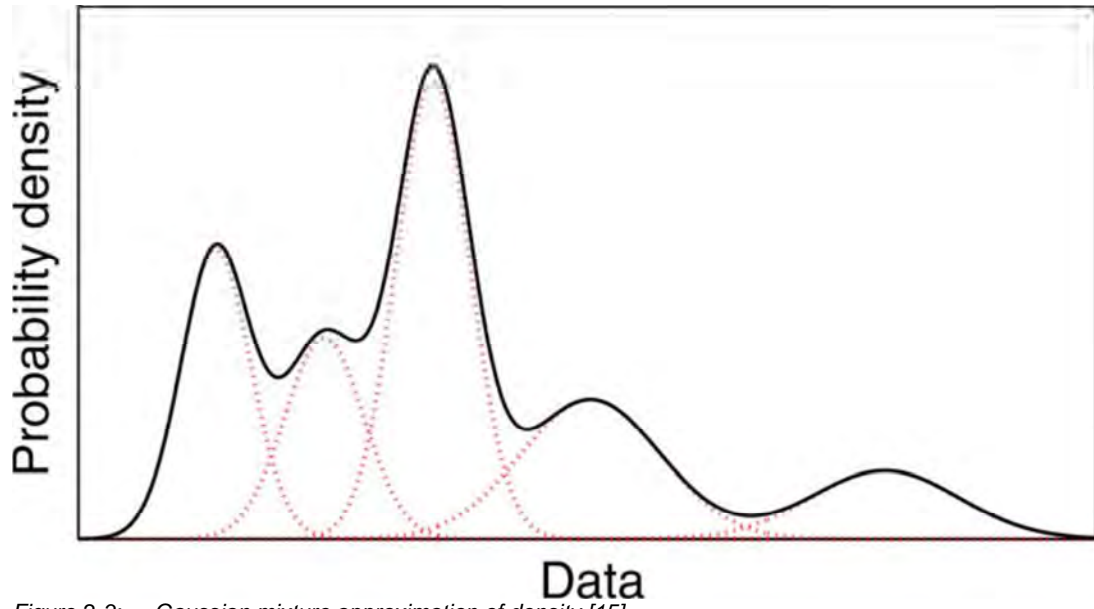


Figure 2-3: Gaussian mixture approximation of density [15]

The GMM PDF is given by:

$$f(z/t) = \sum_{i=1}^{Mc} w_i x f(z|\mu_i, \Sigma_i)$$

Where:

$Mc$  The number of mixture components

$w_i$  The weight of the  $i^{th}$  mixture component

The GMM technique and statistical representation of the load based on the consumer load profiles can be very useful for various distribution system applications such as distribution network planning, probabilistic load flow, load forecasting, customer billing, load management and distribution automation [15].

## INDIA

The Government of India and the United States Agency for International Development signed a joint project agreement on 28 January 2000 calling for the implementation of the Energy Conservation and Commercialization Project (ECO).

The ECO is a four-year programme that targets the reduction of greenhouse gas emissions per unit of electricity generated and consumed in India [16]. It is through this agreement that a load research project was undertaken in India. It was found that domestic and commercial sectors contribute about 42% of the demand as shown in Figure 2-4 adapted from [16].

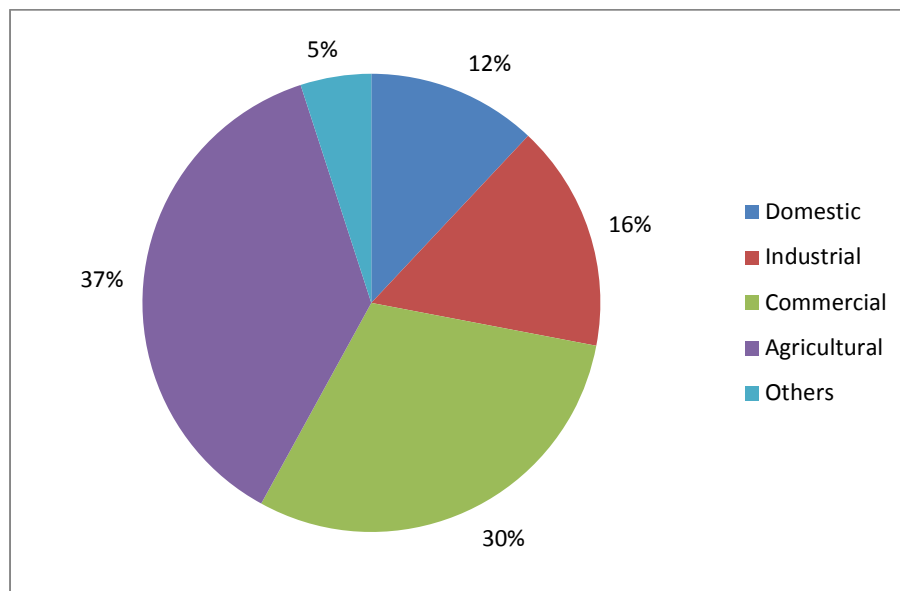


Figure 2-4: Rajasthan electricity demand by sector (percentage of scale) [16]

A load management model using software program named DECIDE2000 was developed. Elements included in the model are as follows:

- Time (short-, medium- and long-term)
- Objectives
- Load shape
- Sectors (residential, commercial, industrial and transmission and distribution)

Information was gathered through survey forms in sectors such as domestic, commercial, small-large industries, agriculture and street lighting as cited in [16].

In addition to the information given above regarding load research project, a study was conducted in India on the 11 kV Chetana feeder supplying 6 335 consumers of which 90% are residential consumers [17].

During winter season, fans and air conditioners are not required, but heating equipment such as heaters is important. Whereas in the summer season the air conditioner is an important equipment for consumers [17].

It can therefore be deduced that weather conditions play a critical role in the modelling of residential loads, therefore, meteorological variables such as temperature, humidity and wind pressure are driving variables to the electricity consumption [17]. This relation is shown in Figure 2-5 where the regression analysis was carried out.

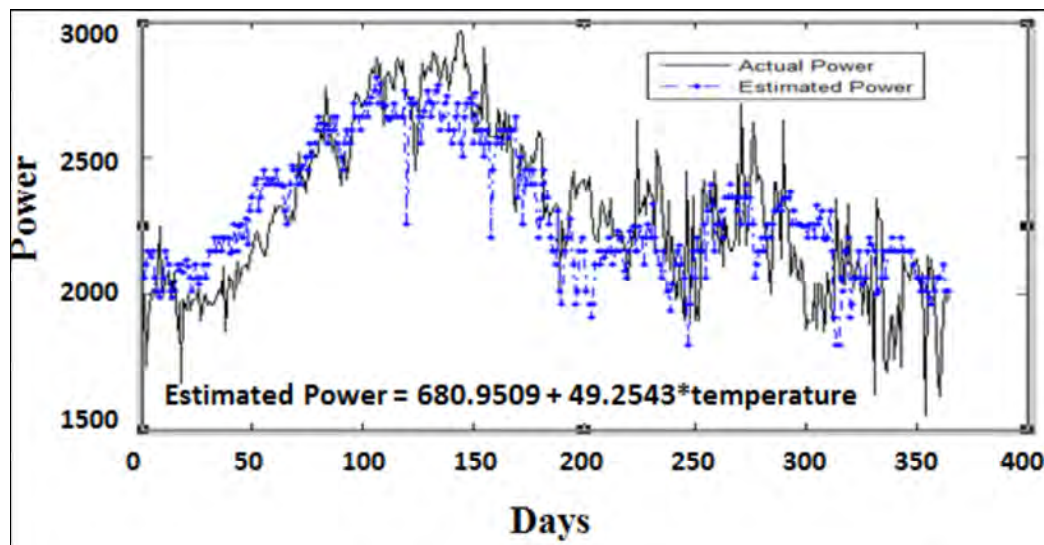


Figure 2-5: Gaussian mixture approximation of density temperature power curve for 365 days [17]

The equation obtained is:

$$P = 680.9509 + 49.2543 \times \text{temperature}$$

By using simple regression, the difference between actual and estimated power is calculated for minimum power, which is 264 kW [17].

### **BRAZIL – SÃO PAULO**

A study was undertaken in São Paulo, Brazil, to determine the daily load curves based on field measurements of residential, commercial and industrial consumers

[15]. It was cited that individual consumer's load curves were measured in periods of approximately 15 days [18].

It is difficult to characterise the peak as it comprises an analysis of diversity: the customer's own diversity, or the diversity among this customer and other customers of the same area.

It is relevant to mention that the extreme daily temperature in this region varies from 35 °C in summer to 10 °C in winter. However, the energy consumption variation due to weather is less than 10% [18].

The representative daily curves from the utility and by consumption range were defined for the residential consumer class. For each utility, the singular ranges were grouped and were finally: 0–50; 51–200; 201–300; and 301–400 kWh per month.

Figure 2-6 shows mean and standard deviation curves for one of these ranges. The high standard deviation values are due to the diversity in the use of electric appliances, mainly the geyser.

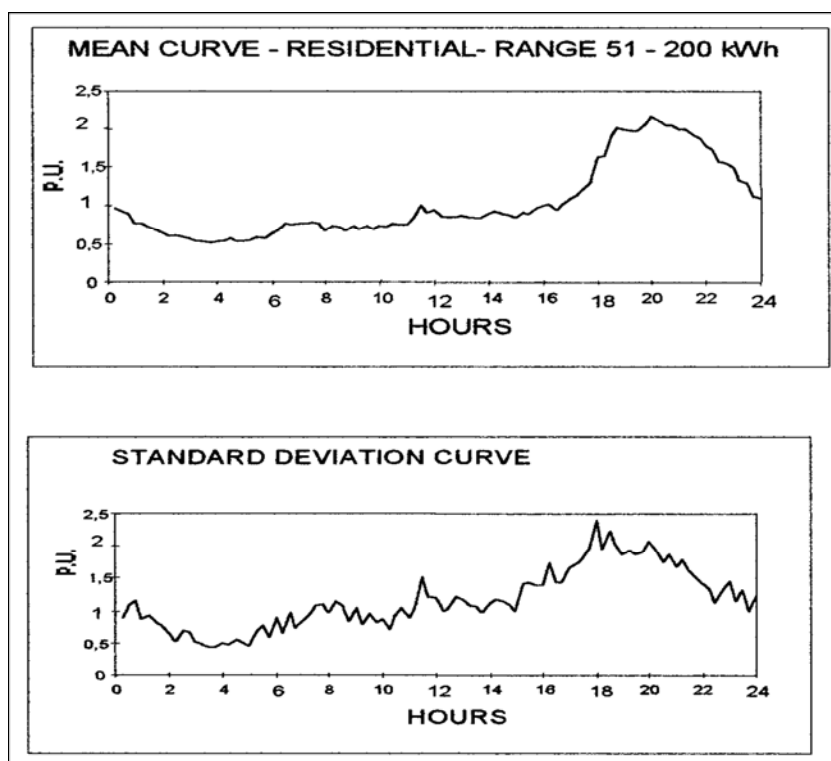


Figure 2-6: Residential consumer range 51–200 kWh per month – mean and standard deviation curve [18]

A daily load curve with a certain probability of not being exceeded can also be established by assuming a normal distribution of values, applying the expression:

$$F(t) = M(t) + kS(t)$$

Where  $k$  is the value in a Gaussian distribution table that establishes the probability percentage, for example, for  $k = 1.3$ , probability = 90%.

The loading representation of equipment by their mean and standard deviation curves is useful for engineering calculation and statistical analysis. A performance criterion can also be established based on probabilistic values.

## CANADA

A small pilot project was undertaken in 20 houses using a convenience sample rather than a stratified random sample [19]. The methodology generalises to samples chosen using standard population sampling techniques. It is cited that the resolution for the measurement device used was 6 seconds.

Given the high variability of the home loads, the information on parameterisation was obtained from a local utility. These parameters were the size of the house and the nature of heating or cooling systems [19].

For the purpose of sizing transformers in the distribution system, a representation set of continuous-time Markov models was chosen. In a continuous-time Markov process, the system remains in the previous state for a period of time before it transitions to a new state; these time periods are distributed exponentially [19].

Dynamics of a  $k$ -states Markov process is represented by a  $k \times k$  transition rate matrix,  $Q$ , where  $q_{ij}$  is the rate of departing from state  $i$  to state  $j$ . The transition rates of each state should sum to zero; therefore,  $q_{ij}$  is defined as:

$$q_{ii} = - \sum_{j \neq i} q_{ij}$$

The following expression was then used to compute the  $Q$  matrix from the clustered home load:

$$q_{ij} = \frac{\text{No. of transitions from } R(i) \text{ to } R(j) \text{ in clustered load}}{\text{Total time spent in state } i \text{ before a transition to state } j}$$

The electric load of a home is modelled using  $k$ -state continuous-time Markov process defined by the  $\langle Q, R \rangle$  tuple.

Figure 2-7 shows the on-peak home load generated from the on-peak model of Class 1. The peak load generated from the model was compared with the actual measurement on-peak load and were found to be similar.

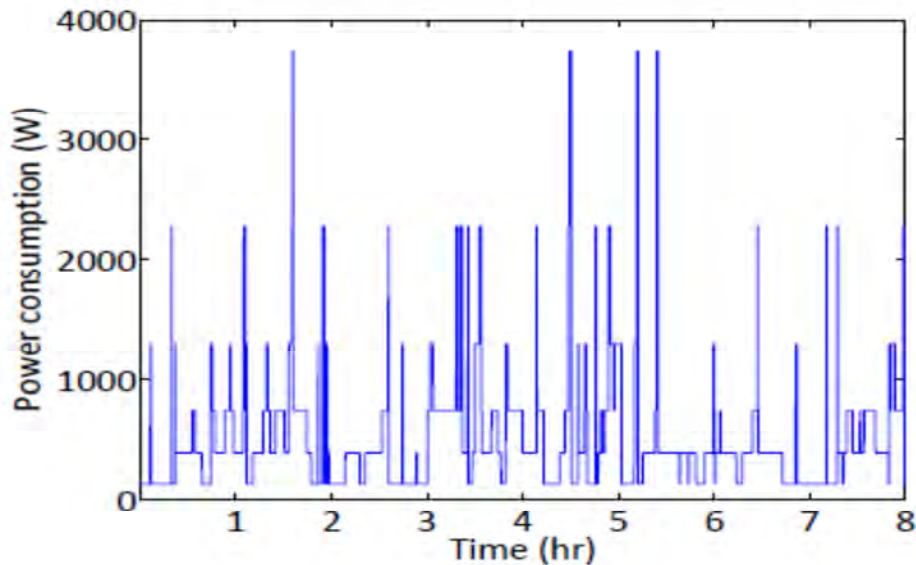


Figure 2-7: On-peak load trace [19]

It was cited in [19] that per class  $k$ -state Markovian reference models can be derived for different periods of the day. It was also cited that these models are accurate enough for transformer sizing.

## **2.6 CONCLUSIONS**

Upon reviewing the literature and information from international countries, the conclusion is drawn that load modelling remains an important aspect of network design and planning. All researchers concur regarding the complexity of the residential sector.

## **CHAPTER 3: VARIOUS ELECTRICAL LOAD MODELS**

### **3.1 PREAMBLE**

With the introduction and advancement of geographic information systems, the designing process of low-voltage networks is also changing. More information about the equipment as well as tools for load flow analysis are available. Reliable load models are required to perform these calculations [8].

A significant amount of work previously has previously been done in load modelling; however, with the sophistication of technology and network expansion requirements, a continuous review of load models is critical. This chapter provides an outcome of reviewed load models that are applicable particularly to the South African context.

### **3.2 EVALUATION OF SOME LOAD MODELS**

In recent years, the interest in load modelling has continuously been increasing and power system load has become a new area for researching power systems stability. Several studies have shown the critical effect of load representation in voltage stability studies and therefore the need of finding more accurate load models than traditional models [20, 21].

The use of dynamic load models has become increasingly more popular than static load models. Although knowledge has been acquired from power system load in recent years, it is one of the most difficult and unknown areas of study amid power system models. This is because of the diverse and complex load components, the high distribution and variation during the time of day and year, weather and the lack of information for the load [21].

The procedure for identifying a load model is shown in Figure 3-1 (as described by [22] from a Co-operative Education Seminar at the University of Western Australia). The project is broken down into sub-tasks.

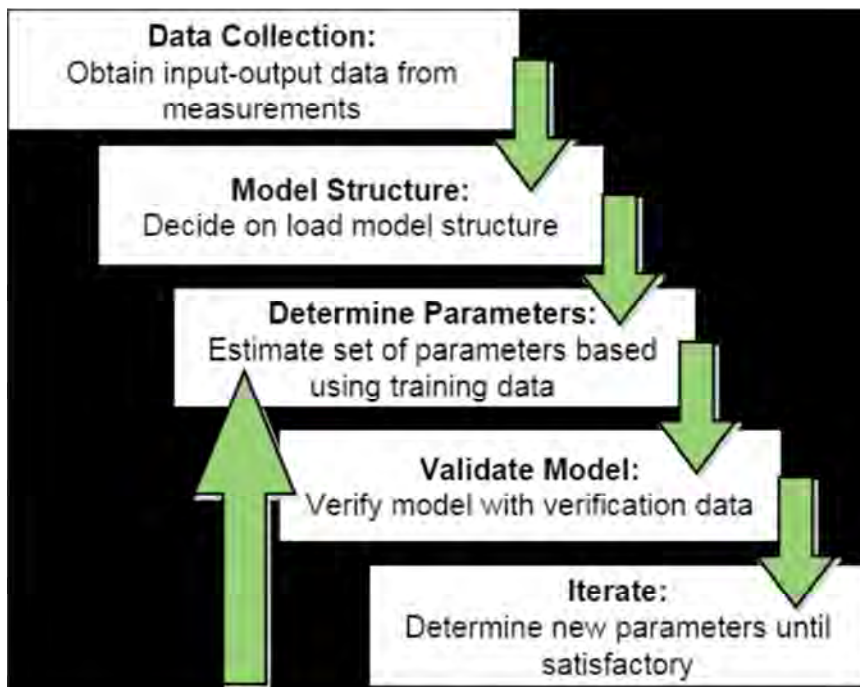


Figure 3-1: Algorithm for determining load models

A continuous examination of load models is necessary because of the dynamic environment where these models are applied. This section provides a summary of the examined state of the art load models.

### POLYNOMIAL MODEL OF KEY APPLIANCES [23]

Table 3-1 shows some of the load models of key appliances in the residential sector. These load models describe the relationship of real power consumption with respect to the service voltage.

Table 3-1: Real power equations of appliances for residential area

Type of appliances	Load model
Lamp	$P = 1.0 + 0.6534.\Delta V - 1.650.\Delta V^2$
Electric pot	$P = 1.0 + 0.3769.\Delta V + 2.003.\Delta V^2$
Refrigerator	$P = 1.0 + 1.3958.\Delta V + 9.881. \Delta V^2 + 84.72. \Delta V^3 + 293. \Delta V^4$
Washing machine	$P = 1.0 + 0.1.2786.\Delta V + 3.099. \Delta V^2 + 5.939. \Delta V^3$
Clothes dryer	$P = 1.0 - 0.1968.\Delta V - 1.650. \Delta V^2 - 28.32. \Delta V^3$

Type of appliances	Load model
Television	$P = 1.0 + 1.2471.\Delta V + 0.562. \Delta V^2$
VCR <sup>4</sup>	$P = 1.0 + 1.1116.\Delta V + 2.633. \Delta V^2$
Fan	$P = 1.0 + 0.7101.\Delta V + 2.133. \Delta V^2$

Considering the power factor of those appliances as nearly 1, it is possible to derive the relationship of normalised current ( $\frac{I}{I_0}$ ) with voltage deviation  $\Delta V$  and normalised power ( $\frac{P}{P_0}$ ).

$$\Delta V = \frac{V-V_0}{V_0} = \frac{V}{V_0} - 1 \rightarrow \frac{V}{V_0} = \Delta V + 1$$

$$I = \frac{P}{V} \wedge I_0 = \frac{P_0}{V_0} \rightarrow \frac{I}{I_0} = \frac{PY_0}{V_0 Y}$$

$$\frac{I}{I_0} = \frac{P/P_0}{\Delta V + 1}$$

Where:

$\Delta V$  Normalised voltage deviation from rated voltage

Subsequently, a relationship of normalised current and voltage deviation can also be expressed for these appliances.

### STATIC LOAD MODELS [24]

A static load model expresses the active and reactive powers as a function of voltage (magnitude and/or frequency). The load model could be a stationary or quasi-stationary representation of the load. The following models are commonly used:

---

<sup>4</sup> Video cassette recorder

*Constant power*

A load model, where the active and reactive powers are independent of variations in the voltage magnitude:

$$\frac{P}{P_0} = \left(\frac{V}{V_0}\right) = 1$$

$$\frac{Q}{Q_0} = \left(\frac{V}{V_0}\right) = 1$$

*Constant current*

A load model where the active and reactive powers vary directly with the voltage magnitude:

$$\frac{P}{P_0} = \left(\frac{V}{V_0}\right)$$

$$\frac{Q}{Q_0} = \left(\frac{V}{V_0}\right)$$

*Constant impedance*

A nonlinear load model where the active and reactive power vary with the square of the voltage magnitude:

$$\frac{P}{P_0} = \left(\frac{V}{V_0}\right)^2$$

$$\frac{Q}{Q_0} = \left(\frac{V}{V_0}\right)^2$$

*Static polynomial*

A nonlinear load model where the active and reactive power variations to voltage magnitude are usually a combination of the three models mentioned above:

$$\frac{P}{P_0} = a_0 + a_1 \frac{V}{V_0} + a_2 \left(\frac{V}{V_0}\right)^2$$

$$\frac{Q}{Q_0} = b_0 + b_1 \frac{V}{V_0} + b_2 \left(\frac{V}{V_0}\right)^2$$

Where  $a_0$ ,  $a_1$ ,  $a_2$  and  $b_0$ ,  $b_1$ ,  $b_2$  are constants and parameters of the load models. The sum of the parameters equals 1:

$$a_0 + a_1 + a_2 = 1$$

$$b_0 + b_1 + b_2 = 1$$

The parameters indicate how nominal power is divided into constant power, current and impedance loads.

### 3.3 LOAD MODELS IN SOUTH AFRICAN CONTEXT

To understand the load models, the behaviour of residential loads has to be studied [20]. Domestic loads are stochastic [5].

In low-voltage networks supplying relatively few customers, the errors in voltage drop calculations can be large due to inadequate treatment of the stochastic nature of the load [9].

Below are some of the load models relevant to the South African context. South Africa is a developing country and therefore the vast majority of residential customers use resistive loads.

#### CURRENT MODEL

The consumer's load can be thought of as:

- Resistance connected to the network
- Current flowing from the feeder through the load
- Power drawn from the feeder

Following basic Ohm's law:

$$V = IR$$

Modelling the load as constant resistance results in the following formula:

$$R = \frac{V}{I} = \text{Constant}$$

It is important to note that from the impedance, ( $Z = R + jX$ ), only  $R$  is considered because of the type of appliance penetrating the electrification customers, namely, resistive load. Hence the unity power factor.

A change in  $\delta V$  in the voltage at the load terminal will cause the current to change according to:

$$\frac{\delta I}{I} = \frac{\delta V}{V}$$

Table 3-2 relates to a single section of a feeder with a source voltage of 230 V and a voltage drop of 10%. The terminal load is a nominal load of 3 kVA at 230 V, which is equivalent to a current of 13.04 A or a resistance of 17.63  $\Omega$ .

Table 3-2: Effect of modelling the load as resistance, current and/or power

Load Model	Scenario 1 17.63 $\Omega$	Scenario 2 15.87 $\Omega$	Scenario 3 14.28 $\Omega$
<b>Current in load</b>	11.74 A	13.04 A	14.49 A
<b>Power in load (VA)</b>	2 430 VA	2 700 VA	3 000 VA
<b>Power input to feeder (VA) at 230 V</b>	2 700 VA	3 000 VA	3 333 VA

As the behaviour of domestic consumer loads conforms quite closely to the current model, it is practical and sufficiently accurate to represent the loads as characteristic currents.

### LOAD PROFILE MODEL

The hourly load profile model shown in Figure 3-2 was derived from filtering, analysing and processing load readings collected over the period 1994–2004. It builds on a consumption model that relates household income, time electrified, floor area and free basic electricity to average seasonally adjusted household consumption, which is derived from the collected load profile data [25].

The higher household income group is clearly temperature sensitive and has a very different profile shape than the lower income group [25].

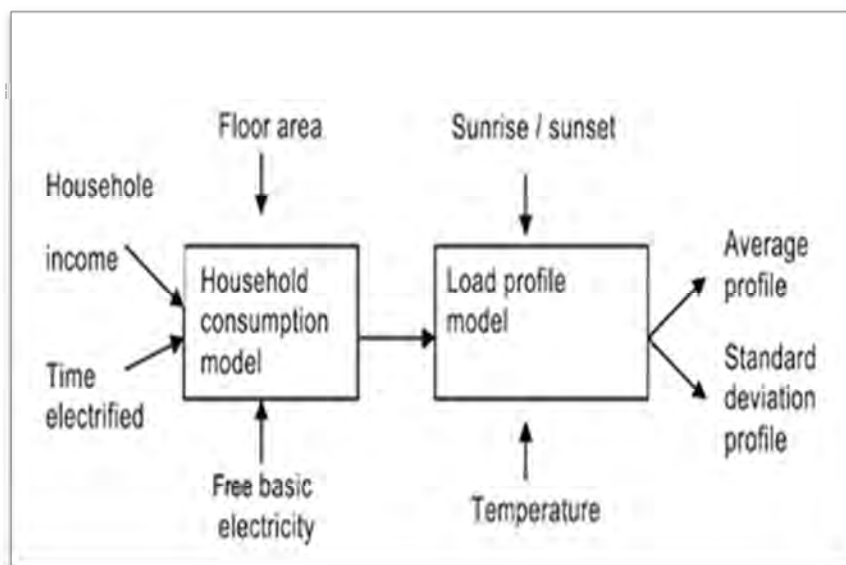


Figure 3-2: Structure of load profile model

Figure 3-3 compares the average daily profiles for two consumption groups, namely, R1 000 per household per month and R10 000 per household per month, for summer (M2) and winter (M6).

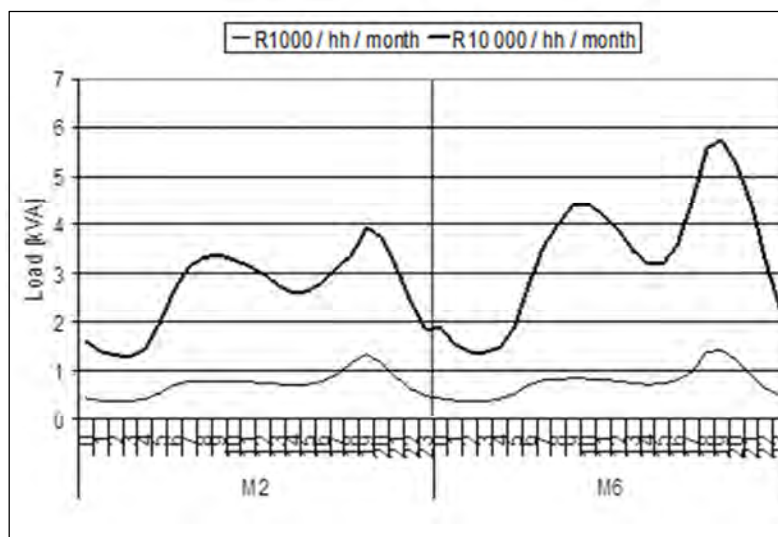


Figure 3-3: Average daily profiles for consumers [25]

The higher income groups have higher energy consumption than the lower income groups. This is observed in the data gathered through socio-demographics and the load profile model in Figure 3-2 where household income plays a critical role in the household energy consumption.

There is a direct correlation between household income and household energy consumption because of access to appliances including electric geysers. However, it is observed that higher income groups are more inclined to afford energy efficient appliances and alternative sources of energy such as solar (geysers) and gas as a result the electric consumption (kWh) is reduced. This observation is important to be considered for network planning in terms of impact thereof.

### **PROBABILISTIC LOAD MODEL**

Load system in the power flow study is usually performed using a deterministic or probabilistic model [26]. Hence, a probabilistic load model for residential consumers is introduced in this section. The model represents the load currents for a community over a period of time.

The largest source of uncertainty in low-voltage distribution design is in the modelling of the design loads. An effective way to deal with uncertainty is to use probabilistic rather than deterministic design methods [2].

The load current of each individual consumer can be represented with an average value and a standard deviation value [8]. A range of possible load parameters might be known for a community, but the load parameter of a specific consumer is uncertain [8].

Residential loads can be approximately modelled as constant current in static load flow studies. The proposed load model assumes that the loads are constant current for all consumer groups. For very low income consumers, this assumption might give overestimates of the voltage regulation and losses.

Load currents at maximum demand, or any other instant, are statistically distributed. This distribution of currents can be represented as a histogram of frequency of occurrence (or probability) against current (in ampere).

A statistical expression, known as a probabilistic distribution function (PDF) can be derived from the histogram. A common PDF is the Gaussian or normal PDF shown in Figure 3-4 [2].

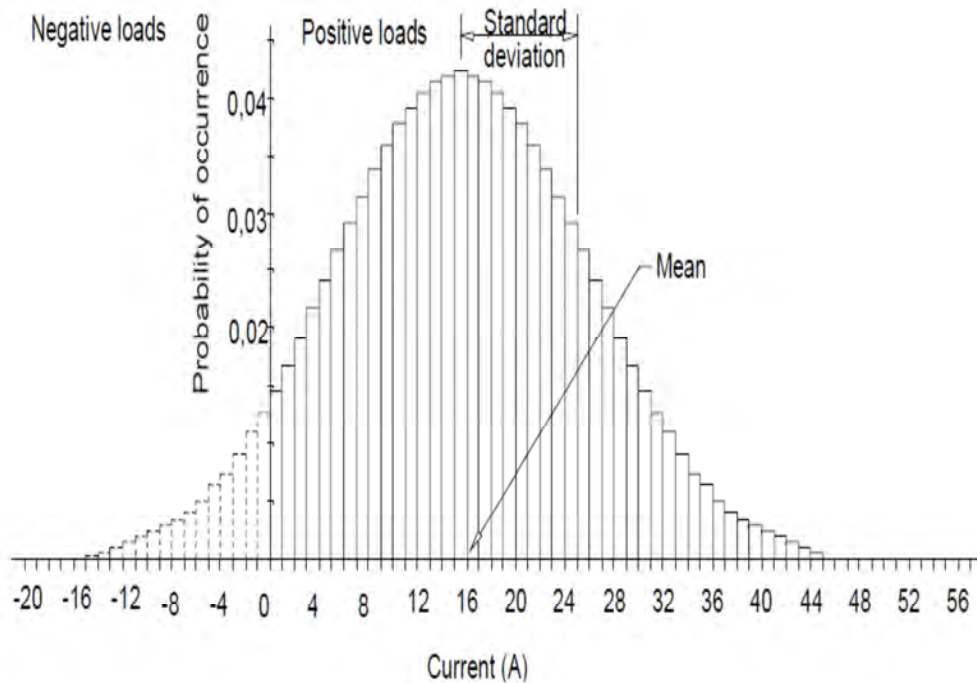


Figure 3-4: Gaussian PDF curve [2]

While this symmetrical description is suitable for a large number of combined loads (>30), it is generally unsuitable for smaller groups (as in reticulation design). In these cases, the PDF of the load currents might be skewed to the right or left as shown in Figure 3-5.

Two statistical parameters are required to describe a symmetrical distribution such as the Gaussian PDF, but three parameters are needed when skewness is included.

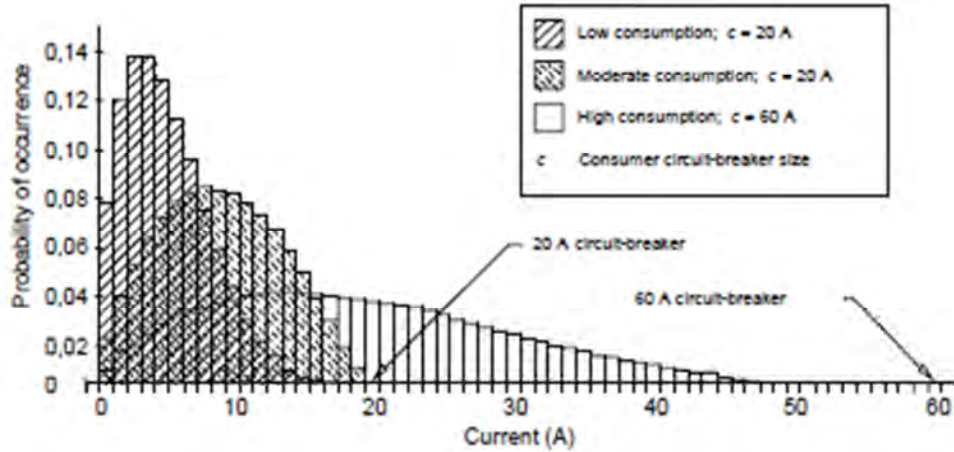


Figure 3-5: Gaussian PDF skewed to left [2]

A convenient PDF for this purpose is the beta PDF with parameters (Herman-Beta method [27])  $a$ ,  $b$  and  $c$ ; a family of curves can be derived that will fit most practical load distributions.

The mean value of the beta PDF is given by:

$$\mu = c \frac{a}{a+b}$$

Where:

$c$       Scaling value – circuit breaker size

Where the load data are available,  $a$  and  $b$  parameters can be derived for any given values of  $c$ , using the mean ( $\mu$ ) and the standard deviation ( $\sigma$ ) of the data.

$$a = \frac{\mu(c\mu - \mu^2 - \sigma^2)}{c\sigma^2}$$

$$b = \frac{(c - \mu)(c\mu - \mu^2 - \sigma^2)}{c\sigma^2}$$

Upon calculating the parameters, the estimated maximum demand (kVA) [2] of the residential load can then be calculated using the formula below.

$$L = 0.23 \times N \times \frac{c}{a+b} \left[ a + 1.28 \sqrt{\frac{a \times b}{N(a+b+1)}} \right]$$

Where:

- $L$                     The maximum load in kVA
- $N$                     The total number of consumers
- $a, b$  and  $c$         Load current model parameters

Load estimation for urban or rural domestic consumers is very important in the cost of the electrification system. Overestimation will result in overcapitalisation while underestimation results in a poor quality of supply, which leads to expensive reinforcement later.

The probabilistic load model was the most suitable model for the South African context because of the cost-effective measures to be considered by network designers and planners during electrification.

Network designers and planners usually know the value of  $c$  based on the circuit breaker controlling the individual loads. Typical values of ADMD – simultaneous maximum demand of a group of customers divided by the number of consumers – can therefore be derived from the load model based on similar communities.

ADMD is the dominant parameter in feeder analysis where the number of customers is large (sample of more than 60 customers).

### **APPLIANCE-BASED MODEL**

Many researchers in residential load modelling takes a top-down approach while other researchers use a bottom-up approach. An appliance-based model is a bottom-up model, which simulates a time profile per appliance per household [28].

Modelling appliances can best be done when average load values are known as stated in [28]. The duration of the appliance usage can therefore be based on practical experiences from everyday life.

Household size (space area) and appliance penetration (usage) play a critical role in load modelling, this is also discussed in Section 4.4 Figure 4-5.

Figure 3-6 indicates the results of one simulation and its associated adjustment against a reference load profile. It was cited in [28] that the simulation was done for 500 households compared with a reference weekday load profile with a geyser ripple control present.

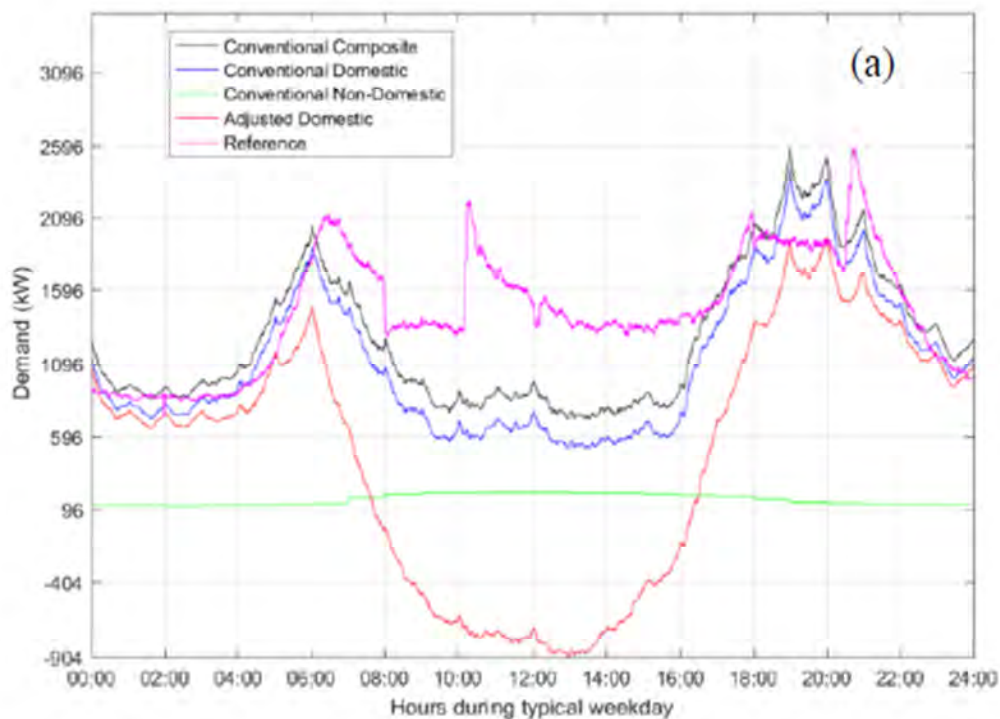


Figure 3-6: Simulated weekday load profile (black line) [28]

Figure 3-7 indicates the results of one simulation and its associated adjustment against a reference load profile. Reference weekday load profile is shown in Figure 3-7 without a geyser ripple control [28].

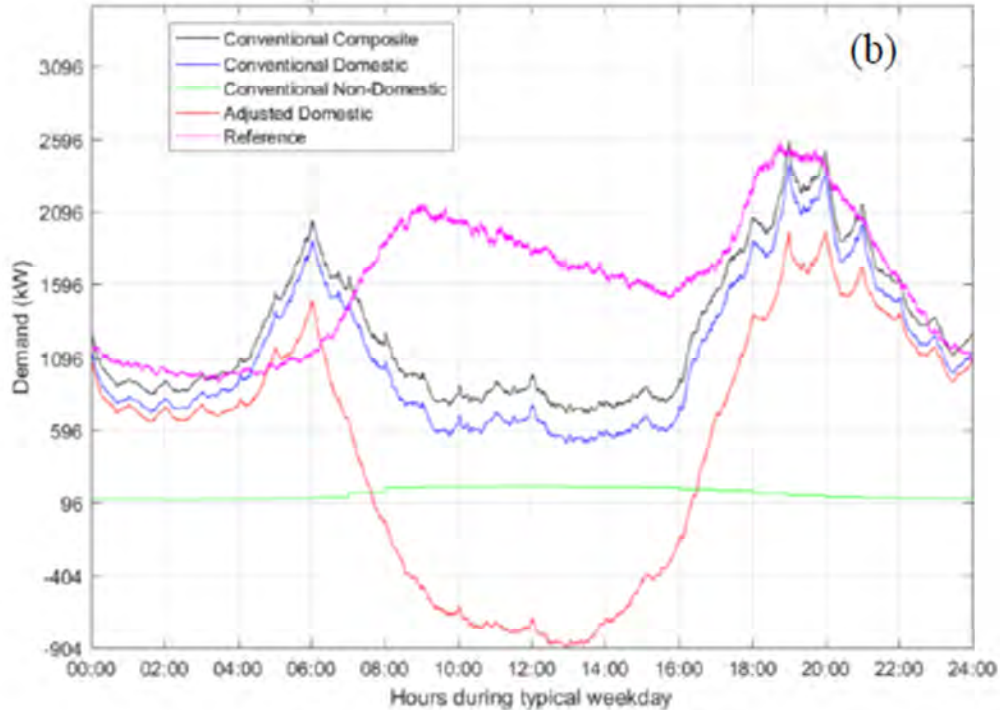


Figure 3-7: Simulated weekday load profile (black line) without any load control [28]

The aim of the reference curve in Figure 3-6 and Figure 3-7 is to ensure the gradient of the calculated profile leading up to the evening peak as well as the width of the peak match the gradient of the reference curve [28].

This approach is important for network planning and DSM as it assists in identifying critical appliances and how these appliances impact the interventions for demand management.

The theory also suggests that the currents drawn by households at the time of the evening peak represent a beta distribution as shown in Figure 3-5. This coincides with Figure 3-8 simulated for 500 consumers.

The conventional and adjusted load profiles are shown in Figure 3-8 for these consumers and the graph (in red) indicates beta distribution curve behaviour [28].

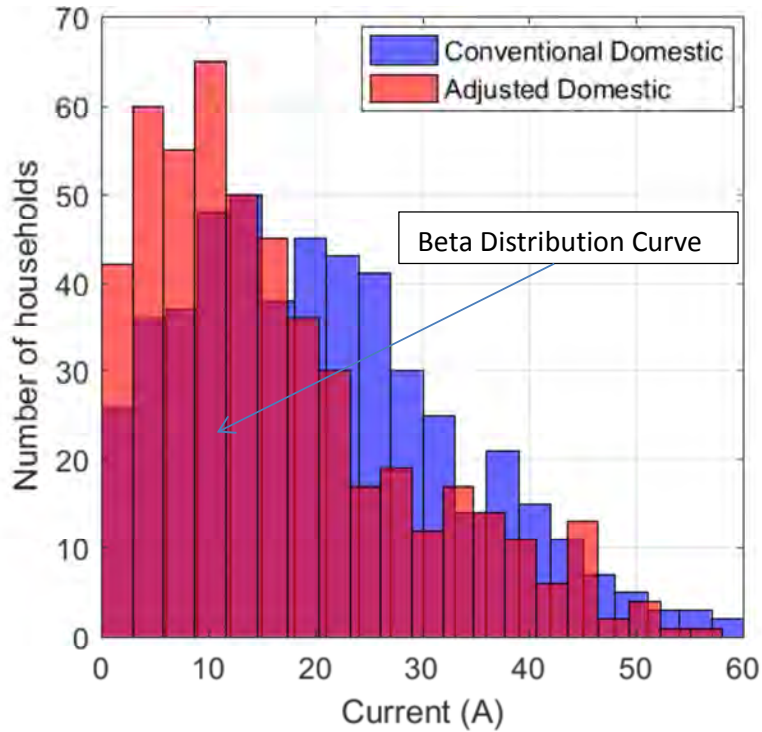


Figure 3-8: Distribution of currents drawn by 500 consumers [28]

It is therefore concluded that the model is suitable for assessing the impact that “green” measures will have on load profiles as the developed model satisfies the theory checks. The model can generate load profiles representing a community based on random electricity consumption behaviour within general society boundaries [28].

### 3.4 CONCLUSIONS

The design and planning of electrification networks are most effectively expedited when appropriate and accurate models of the circuits and the loads are available [26].

A probabilistic load model for residential consumer load currents is presented. The model explains the variation in the load current for a period of time and the differences between consumers [29]. This model indeed depicts a true reflection of the residential customers supplied by Eskom.

It was also cited in [30] that the Herman-Beta method is the most accurate probabilistic approach for dealing with various load types and consumer connection arrangements. In the lower income group, the heaviest loads are resistive resulting in unity power factor. Hence the loads are considered as currents, this is also true for the purpose of voltage drop calculation at unity power factor.

The connection of actual loads to the system should be accurately modelled, the Herman Beta algorithm is particularly advantageous to use for voltage drop calculation. The Herman Beta algorithm was compared with other methods as cited by Gaunt and Sellick in [31] and was found to be more consistently reliable for voltage drop calculations, some methods are summarised as follows:

- Monte Carlo Simulation: The load model is a beta distribution probability function for consumer currents. It requires large numbers of simulations to be run and they are time consuming for setting up each network. Therefore they are usually not appropriate for design or network operations monitoring.
- British method: Analytical algorithm using empirical formulas to cater for unbalance and diversity. This method overestimates the voltage drop and can cause oversized feeder conductors.
- Loss of Diversity method: This method was derived from Monte Carlo simulations, it uses load models defined as Normal distributions with different slenderness factors ( $s = \mu/\sigma$ ). This algorithm does not take into account the consumer configuration. The method was found not to be suitable for single phase feeders.

There is a need to re-evaluate the ADMD calculation because of recent development in the residential sector. The focus is not on new electrification anymore, but rather on refurbishing and strengthening existing networks because of in-fills.

Benchmarking through international standards was achieved through the literature review. Accessing much-needed information available assisted in ensuring competitiveness and utilising proven techniques in load modelling.

# CHAPTER 4: DATA ACQUISITION OF ELECTRICAL LOAD

## 4.1 PREAMBLE

Part of the problem in the residential complex environment is the unavailability of data because of the metering infrastructure. To adequately model residential loads, one requires a significant amount of credible and validated data. This chapter provides the data acquisition process, type of data acquired, storage and dissemination and the technology used to acquire data.

## 4.2 TYPES OF DATA ACQUIRED

The development of a sound statistical database of residential loads requires the synchronised measurement of individual customer loads. The data have to be matched by relevant demographic surveys [8]. Hence the data gathering process is twofold.

### SOCIO-DEMOGRAPHIC SURVEY

Conceptually, any non-electrical parameter that may affect the load should be identified and evaluated. This is particularly important for those parameters that have the greatest effect on the load a customer is likely to take.

Unlike electrical parameters, there is no device that will record most demographic parameters. This information can usually only be gathered by personal interviews.

There are two issues that require attention in demographic data collection:

- The questionnaire: A suitable questionnaire must be configured that includes all the relevant questions for collecting demographic information. Some skill is required in formulating the questions so that the information can be obtained in a non-threatening manner.
- The interviewer: Information must be as accurate as possible. The interviewed customer must understand the questions asked. It is the responsibility of the interviewer to ensure that the responses are valid.



## METER DATA

The load data may be formulated in several ways according to the requirements of applications. The most important specifications for load data are:

- System location: customer site, low-voltage network, transformer, etc.
- Customer class: industry, service, residential, electric heating, etc.
- Time: time of year, day of week, time of day.
- Dimension: A, kW,  $\cos \Phi$ .
- Time resolution of load recording: 5 min, 15 min, 30 min, 60 min, etc.

The concepts that should be considered when collecting data for load modelling are as follows [5]:

- Representative sample
- Accuracy of data
- Appropriate to requirements
- Simultaneous measurement
- At individual level
- Statistical significance

The data logger records data at a resolution of five-minute intervals and the following parameters are stored:

- Voltage
- Current
- Active power
- Apparent power

Each data logger has three independent channels. All data returned remotely (through GPRS<sup>5</sup>) from the loggers undergoes validation subsequent to each successful data download. When the validation rules are “triggered”, for example when threshold values are exceeded, an alarm is raised [32]. Depending on the

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<sup>5</sup> General packet radio service

nature and severity of the alarm, a “fast” field visit task could be initiated to service the problem.

The data quality reports are ideally produced monthly. The quality checks focus on aspects such as zero values and missing data channels. The data quality report forms the basis for other site visits.

### 4.3 STORAGE AND DISSEMINATION OF LOAD DATA

The system master station is a facility where the load data from the loggers can be accumulated and stored. This is also where the application and communication medium to the loggers can reside. It furthermore provides a possibility of viewing the data, performing preliminary validation and information regarding the success or failure of communication with the loggers on-site.

Additionally, information about the identity of each logger and logging position is stored at the same location as the load data. This capability in the system master station provides the system operator with sufficient information about the general condition of each device. Different applications to achieve this function exist from different suppliers. Depending on the specific needs of the user, the hardware on which they run can be customised to suit the customer or end-user’s specific need.

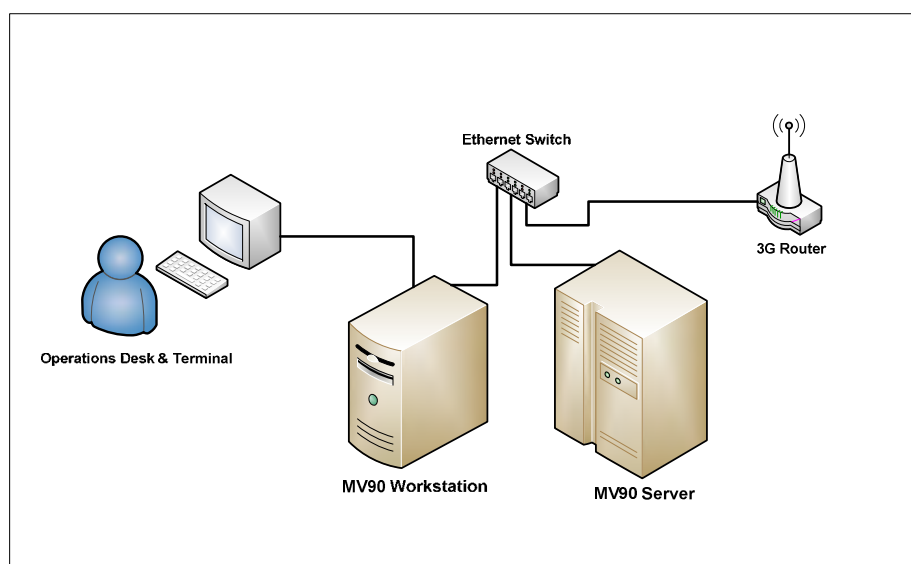


Figure 4-2: Previous information technology (IT) server system

It is common for systems to evolve over time due to technology developments and changing user requirements. The hardware used for this research in Eskom to house the master station has changed over the years, which is indicated in Figure 4-2 and more recently Figure 4-3 [32].

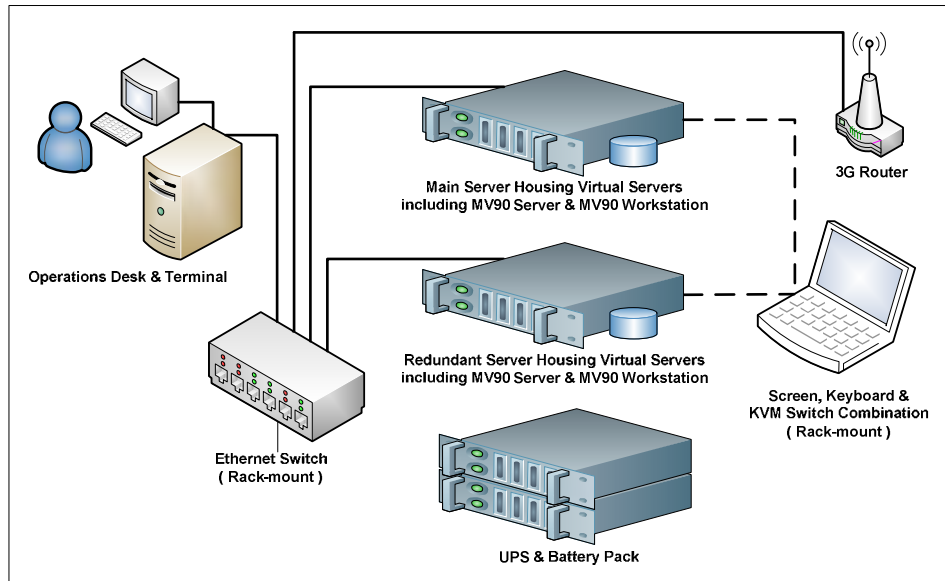


Figure 4-3: Upgraded IT server system

Major considerations to move to the existing software and hardware platform include the following:

- Server rack environment
- Obsolescence of previously used download software application
- Provide for flexibility and growth
- Ease of direct and remote system access
- Redundancy, with two sets of similar hardware with virtual machines
- Three-year on-site hardware support
- UPS<sup>6</sup> for backup and surge protection

<sup>6</sup> Universal power supply

The acquired data is disseminated to various stakeholders through a manual process. Plans are in place to automate the system in the near future. The data is also utilised for various needs and requirements such as:

- Load modelling.
- Load forecasting for the purpose distribution network design, planning and refurbishment.
- Assessment of distribution network for quality of supply (QoS) purposes.
- Design of tariffs for residential sector.
- Research for the development of technologies and other enhancement interventions.

Because of the various uses of data by different stakeholders, it is imperative to develop a central data repository. This requirement is currently in progress and is demonstrated in Figure 4-4. Table 4-1 provides a description of the acronyms used in Figure 4-4.

*Table 4-1: Description of acronyms in the architectural structure*

Item	Acronym	Description	Purpose
1	SAS	Statistical Analysis System	Software for analysis and report writing
2	ETL	Extraction, Transform and Load	Data transfer from one source to another
3	ODM	Operational Data Mart	
4	ODS	Operational Data Store	Enables online data processing
5	MDMS	Meter Data Management System	Transmission dataset from a separate system
6	Tx	Transmission	High-voltage transmission data

The data would be acquired from various data sources, including the data for this research which is labelled Domestic Load Research (DLR) in Figure 4-4. Figure 4-4 is the architectural structure [33] of the Load Studies Data Store (LSDS) with the objective of enhancing data access to all stakeholders.

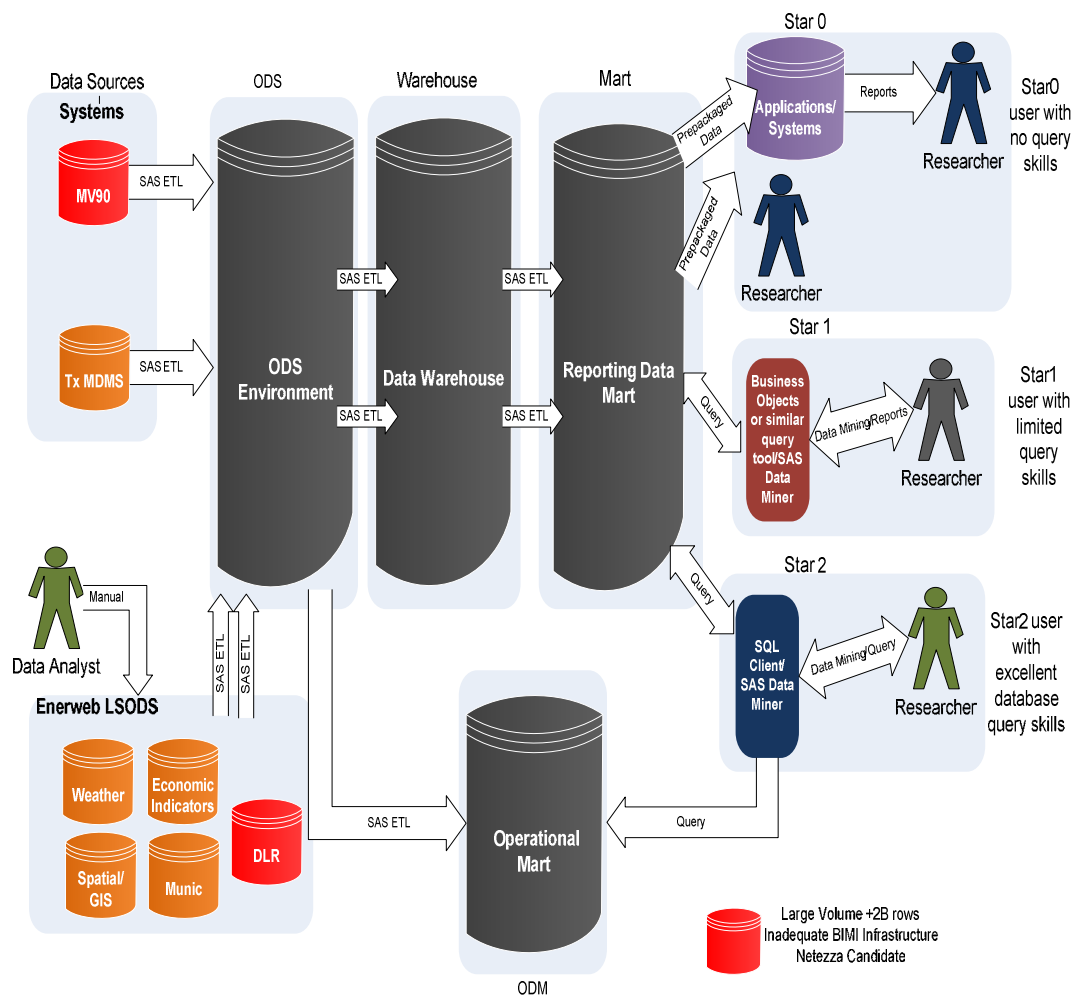


Figure 4-4: Data store warehouse known as LSODS

Other datasets to be acquired are weather data, economic indicators, spatial data, transmission data, etc. Access would be granted to users at three different levels, based on the skills and expertise level, namely, Star0 (no query skills), Star1 (limited query skills) and Star2 (excellent database query skills).

#### 4.4 SAMPLE DESIGN PROCESS

This section discusses the sampling process that was followed during the research. A 100% sampling rate would be ideal; however, because of the cost to be incurred, it is not financially practical. In view of this, a statistical representation of the total population, which consists of Eskom customers, was calculated. The

sampling process was twofold, namely, obtaining the needs and requirements of the business or stakeholder and compiling the sample design.

### **STAKEHOLDER NEEDS AND REQUIREMENTS**

The number of stakeholders who may require information about residential consumer loads was identified. Their requirements were gathered using interviews. A simple questionnaire ensured a degree of consistency in terms of coverage. The questionnaire had the following questions:

- In which planning, forecasting or estimation activities are you (or your department) involved that requires knowledge about residential customers?
- Where do you source this information or knowledge currently?
- Where and who implements the output of this activity (business function)?
- How often is this activity performed, for example, annually or monthly, or is it project based?
- Do you consider a particular type of customer such as electrification in residential?
- What is the focus of the activity – feeder, transformer, sub-regional, regional or national?
- What level of information is required – five-minute profiles, half-hourly profiles, monthly or seasonal?
- What measurements are required – voltage, current, kWh, kVA?
- What other information is used as input into the completion of these activities – weather, tariff, customer classes, network, age of customers?
- Is there any information that is currently missing, any improvement necessary?

The first questions were intended to establish the context of the activity in the business and the latter questions the specific information required. Table 4-2 presents departments of stakeholders within the utility and their areas of activity.

Table 4-2: Stakeholder and areas of activity

Stakeholder	Activity
<b>DSM</b>	Micro DSM
<b>DSM</b>	DSM planning for municipalities and residential sectors
<b>Electrification</b>	Electrification planning parameters
<b>Geobased load forecasting</b>	Load forecasting/planning
<b>Integrated strategic electricity plan</b>	Long-term forecasting
<b>Pricing</b>	Cost of supply
<b>Pricing</b>	Residential standard and tariff design
<b>QoS</b>	Measure and report QoS
<b>Sales forecasting</b>	Sales forecasting: Impacts of GDP, weather, etc.
<b>Treasury</b>	Estimating price elasticity

The needs and requirements vary from one department to another within the utility; however, this variance exists because of the dynamics of the residential consumers.

### **SAMPLE DESIGN**

The sample design was conducted through stratification (the process of dividing members of the population into homogeneous subgroups before sampling) and sizing of the sample.

#### *Stratification*

Stratification of the sample is performed to ensure representation and potentially to improve sample efficiency. The selection of stratification variables is based on the most significant predictors of household demand per half hour, month or maximum per period [34].

Figure 4-5 shows a simplified influence diagram of the residential consumer winter weekday load that was derived from significance testing using load and socio-demographic data for residential consumers collected between 1994 and 2006.

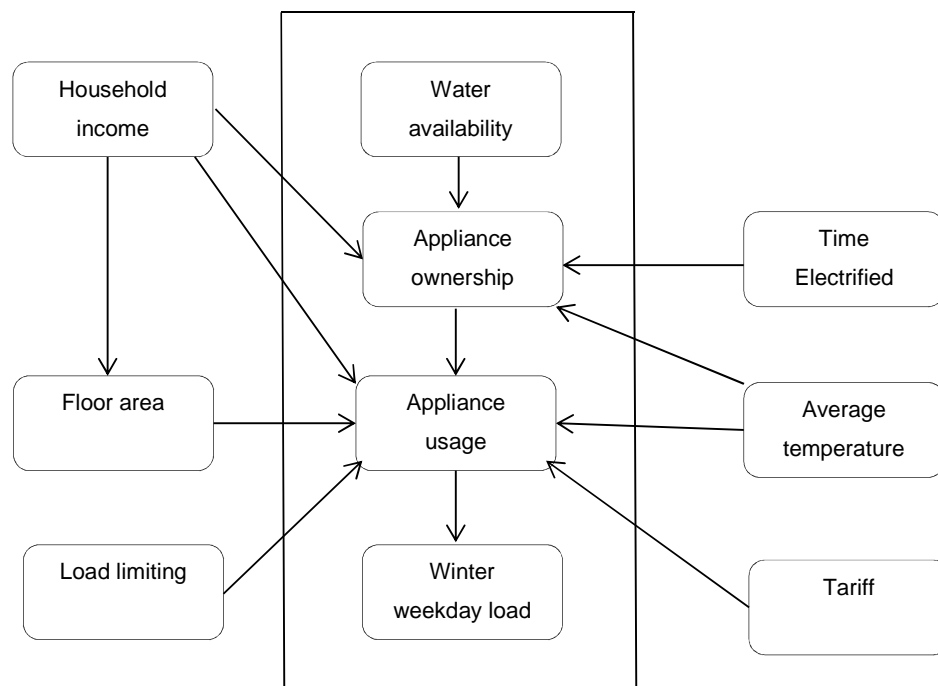


Figure 4-5: Conceptual model of causes and effects of residential consumer winter weekday load [34]

Using linear regression, the following standardised coefficients were obtained for estimating the average winter load [34]:

- Household income (0.75)
- Time electrified (0.41)
- Average temperature (-0.1)

The outcome shows that the major stratification variables should be household income and time electrified.

### Sample size

The collected data was used to fit the various models used to address stakeholder requirements. The regression estimator was therefore used to estimate the sample size. To obtain the sample size the following was specified:

- Percentage error
- Significance ( $\alpha$ )
- Variance explained by the proposed model ( $R^2$ )

The sample requirement for each stratum was calculated based on significance as follows:

$$n_s = (1 - R^2) \left( \frac{z_\alpha \sigma_s}{\epsilon_{pu} \mu_s} \right)^2$$

Where:

$n_s$  Sample requirement for stratum s

$R^2$  Variance explained by the proposed model

$z_\alpha$  Percentile of the standard normal distribution that corresponds to the specified significance ( $\alpha$ )

$\sigma_s$  Standard deviation of consumption in stratum s

$\epsilon_{pu}$  Per unit error

$\mu_s$  Average consumption in stratum s

Figure 4-6 shows the samples size for different proposed  $R^2$  values as a function of the per unit error (significance level of 5%).

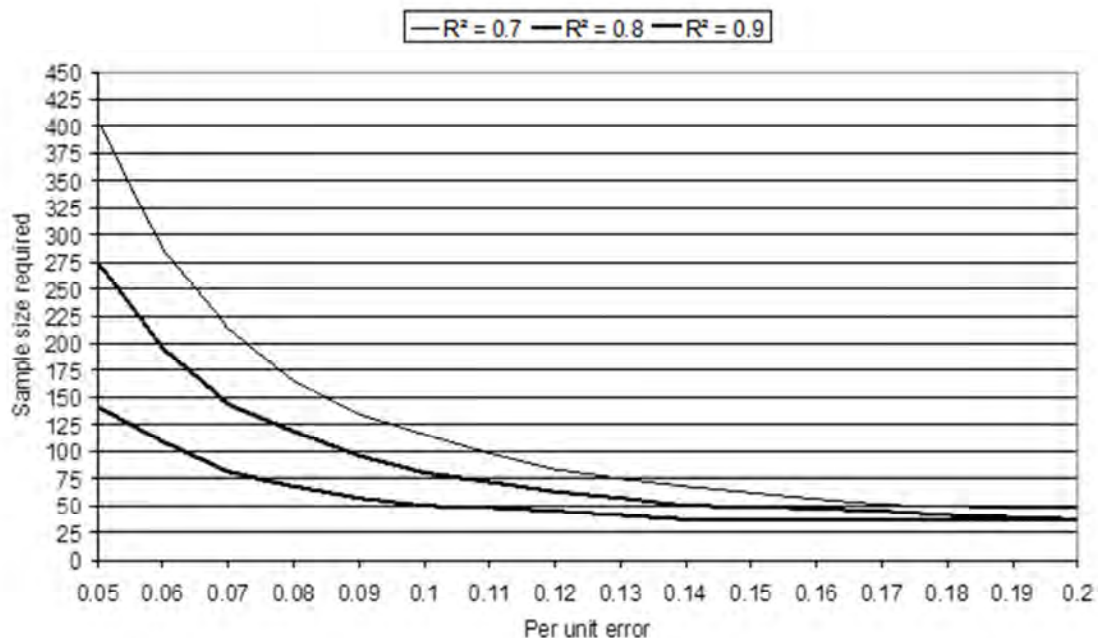


Figure 4-6: Per unit error as per sample size [34]

It is clear that the  $R^2$  and per unit error increase as the sample requirement decreases.

#### *Power of the sample*

A further requirement on the sample size is the power of the sample. This is the probability that the null hypothesis is rejected if a specific alternative hypothesis is true. For multiple regression models, the power can be calculated based on the following:

- Number of variables in the regression
- Sample size
- Effect size that should be detectable – this is calculated from using the amount of variance explained for a particular variable

Figure 4-7 shows sample size as a function of power; to obtain good statistical representation in terms of a sample, a higher power should be attained.

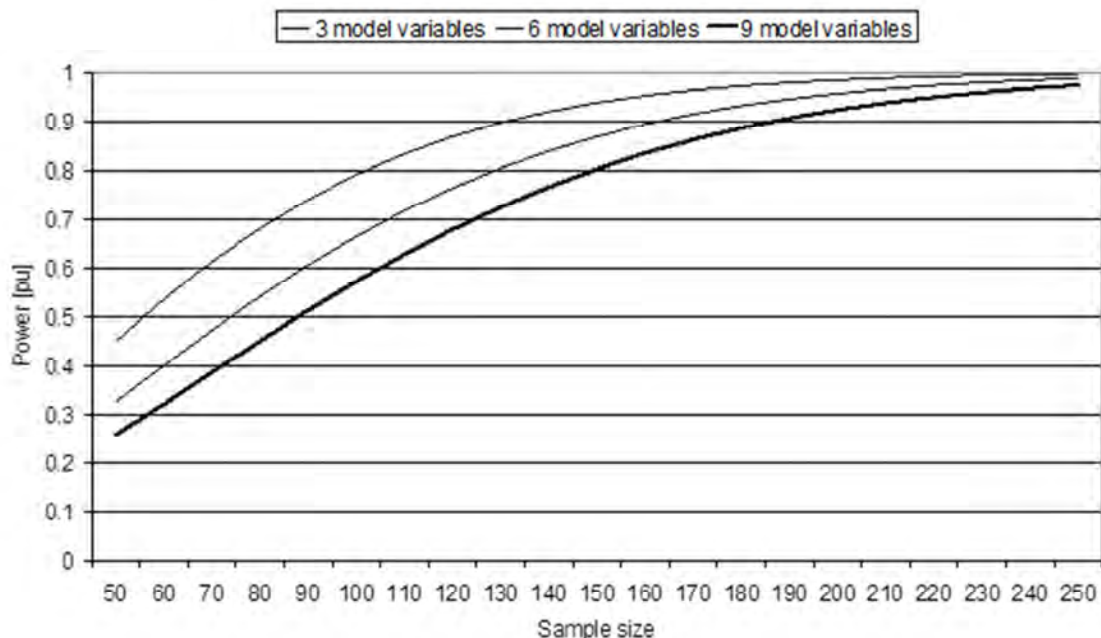


Figure 4-7: Per unit power as a function of sample size [34]

For a sample size of 80, this corresponds to a power of 58%, which is too low. A power of 80% or higher would be acceptable. This can be achieved by increasing the sample size to at least 120.

#### *Site selection*

The sites were selected in accordance with the requirements and needs of the stakeholders. Particular interest was in rapid growth within urban areas and access to electrical appliances.

Sales data was used to identify potential sites in accordance with standardised coefficients, namely, number of years a particular area has been electrified and the household income. Once an area meets the selection criteria, site inspection would be executed. Upon completing the inspection, sites that met the criteria in entirety would be selected for logger installation.

A site is a particular area where a minimum number of 60 customers and a maximum number of 90 customers are sampled. This number is achieved by installing 30 loggers in that particular area with three customers per logger.

## 4.5 TECHNOLOGY FOR DATA ACQUISITION

This section describes the technology used for data acquisition, as well as the position where the loggers were installed. Technology plays a critical role in the data acquisition process. The credibility and quality of data rely on the type of meter, data storage and processing.

A brief description of sites where loggers are installed is also provided.

### OLD TECHNOLOGY USED

The logger in Figure 4-8 used for DLR in Eskom before 2009 was the TRI5001. This was an in-house developed logger which logged five-minute averages of one-phase voltage and the seven channels (currents).



Figure 4-8: Installed old logger showing wires connecting the current transformer (CT)

Direct serial connection was the only means to communicate with this logger to transfer the captured data. This involved travelling to each meter and performing a manual data download.

The availability of a parts and firmware support became onerous and therefore the technology was deemed obsolete. Rewrite of downloading software was initiated [35]. This data logger was phased out in early 2009.

### **NEW TECHNOLOGY**

The researcher played a leading role in 2008 where a study was commissioned to determine a suitable commercially available energy meter/logger to replace the ageing TRI5001 logger [36]. This study mainly considered the following aspects:

- Metering and logging parameter range
- Flexibility to set up logging parameters
- Ease of use
- Accuracy, repeatability and reliability
- Robustness
- Economic viability of solution
- Data storage capability
- Established communication capability
- Ease of integration with multi-vendor data acquisition software

The recommendation from this study was to use the Landis+Gyr ZMD405 energy meter, referred to as the L&G Logger. The logger is shown in Figure 4-9.



Figure 4-9: *Logger kit comprising meter, surge arrester, circuit breaker, box cover with brackets, CT cables and three CTs*

Figure 4-10 shows the same logger with LCD screen showing zeros. The advantage of the LCD screen is that one can manually scroll to check the readings.



Figure 4-10: *Logger kit with LCD screen on*

## INSTALLED SITES

To assist with installations, the L&G Logger was ordered as an installation-ready unit. This unit typically comprises the following:

- Pole-mountable enclosure with brackets
- Kiosk-mounting adaptor plate
- L&G logger with internal GSM<sup>7</sup>/GPRS modem to provide remote downloading through private static access point name
- Isolation circuit breaker
- Surge protection
- Readymade cable harness
- CTs, rating of 100 A/5 A

Figure 4-11 shows an installed logger on a wooden pole on-site. The logger is installed just below the distribution service box.



*Figure 4-11: Logger installed on a wooden pole*

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<sup>7</sup> Global system for mobile communication

Figure 4-12 shows an installed logger on a concrete pole on-site. The logger is installed just below the distribution service box.



Figure 4-12: Logger installed on a concrete pole

While the new data logger is an improvement and provides better functionality, it has increased in size. The dimensions of the CTs also increased.

The robustness of the logger is of utmost importance as these loggers operate under various climatic conditions. There is a seasonality component within a domestic electricity load profile, which is mainly a result of changes in external temperature and daylight hours for heating and lighting homes respectively [20]. It is therefore prudent to install loggers at various climatic conditions. Figure 4-13 shows the geographic locations where the loggers were installed. A total number over of 400 loggers were installed across the country in areas of various climatic conditions.



Figure 4-13: Geographic locations where loggers are installed

Table 4-3 provides sites names and number of loggers installed across seven provinces in South Africa. These sites are Eskom residential customers. A total of 415 loggers have been installed to date with an approximation number of more than 1 000 customers.

It is important to state that the researcher was fully involved in the selection of sites, inspection and installation. This is important to ensure that the researcher is fully conversant with the dynamics and conditions in the field as these impact the research process.

Table 4-3: Sites names and number of loggers installed

Province	Site name	No. of loggers
<b>Eastern Cape</b>	Mcubakazi (near Butterworth)	31
	Hankey	27
<b>Free State</b>	Dipelaneng	30
	Phomolong	30
	Selosesha	30
<b>Gauteng</b>	Bophelong	30
	Wattville	27
<b>Limpopo</b>	GaNkoana	30
<b>Mpumalanga</b>	Matsulu	30
	Vlaklaagte	30
<b>North West</b>	Morokweng	30
	Luka	30
<b>KwaZulu-Natal</b>	Hopewell	30
	Matshana	30

## DATA ACQUISITION SOFTWARE

### *L&G MAP 110 Proprietary Software*

Initially, the free proprietary data acquisition software MAP110 provided by the logger was used to collect data from the new L&G logger. During this period, only a few loggers were deployed in the field and the flow of data proceeded smoothly.

As the population of installed devices grew, it became impossible to access all devices for data collection within the required time frame. The attributes of the software that made it less suitable were the following:

- Manual initiation of meter download; no download scheduling possible
- Only a single meter could download at a time
- Data was not stored in a database, only in separate files per download
- No first-line data validation and reporting tools were available

*Due to the drawbacks listed above, it soon became apparent that another software application had to be found that could support a growing population of loggers. An investigation into data acquisition software addressing the listed drawbacks and to streamline regular data acquisition from multiple loggers led to the adoption of Itron's MV90.*

#### *Itron MV90 Multi-Vendor Software*

Some of the attributes that informed the choice of MV90 being the preferred downloading application are:

- MV90 is widely used in the Eskom environment.
- The application is a multi-vendor solution not limiting the loggers to a single supplier or model.
- MV90 has extensive data validation and reporting capabilities (including substantial interval and reading status/event information).
- MV90 supports scheduling of downloads, with success/fail logging.
- Depending on the communication hardware setup, MV90 can handle data collection from multiple loggers simultaneously.
- Data is stored in a database. Thus, queries and reporting is possible on any historical data.
- Data can be exported and transferred in several formats.

The software has shown tremendous performance to date.

## **4.6 CONCLUSIONS**

By supplying electricity to consumers by the utility, which is an important commodity, the utility is actually transferring important information/data. This information/data, when captured properly, would assist the utility in planning and forecasting. The captured data reveals significant information regarding the supplied electricity, the performance of the network, the usage and penetration of appliances and the behaviour of the consumer. It is therefore concluded that data acquisition should be an ongoing task by electricity utilities.

## CHAPTER 5: RESULTS

### 5.1 PREAMBLE

This section provides the analysis conducted on the collected data and the results. There are currently 14 sites where data loggers are installed. For the purpose of this research, data analysis and discussion of results were limited to two of the 14 sites, namely, Mcubakazi and Matshana.

### 5.2 DATA ANALYSIS

The data gathering process was twofold as discussed in Section 4.2, namely, socio-demographic survey and meter data. In order to achieve a true representation and reflection of the residential customer in terms of electricity usage, appliance penetration and appliance usage, the two datasets had to be linked.

The linking of the two datasets occurred on the database. The logger identification is used to link customer responses year-on-year. A name match based on the co-occurrence of letters is generated to establish whether the household name matches year-on-year [37]. Hence the socio-demographic survey is conducted annually.

Figure 5-1 shows the average percentage match year-on-year for all sites<sup>8</sup> recorded to date between 60% and 80%. In 2014, 14 sites actively gathered data. Figure 5-1 shows the number of sites returning good data. Two sites are returning 80%, three sites are returning 83%, two sites are returning 83%, two sites are returning 88% and the rest are below 78%.

There has been tremendous improvement of data returns since the installation of new technology in 2009.

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<sup>8</sup> Good data returns graph for all sites are provided in Annexure A and Annexure B. The snapshot of data is from Matshana

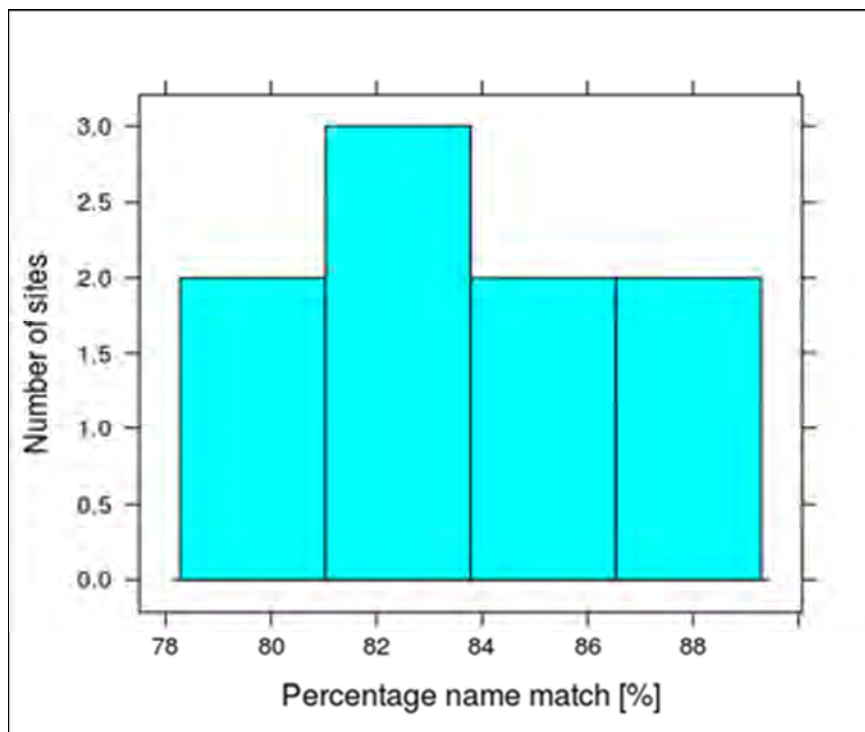


Figure 5-1: Histogram of percentage name match for all sites collected in 2014 [34]

The data is extracted and processed in a separate analysis environment and reporting is done for all sites.

Downloaded data was analysed per site, per logger and per household. The analysis was then cross-referenced with other sites. Figure 5-2 shows the maximum current of all loggers at Mcubakazi for a period of one year, August 2015–September 2016.

As cited in Section 3.3, the behaviour of domestic consumer loads conforms quite closely with the current model, hence the focus of this research is on current, but not only limited to it.

In Figure 5-1 to Figure 5-4, HH1, HH2 and HH3 represent Household 1, Household 2 and Household 3 respectively.

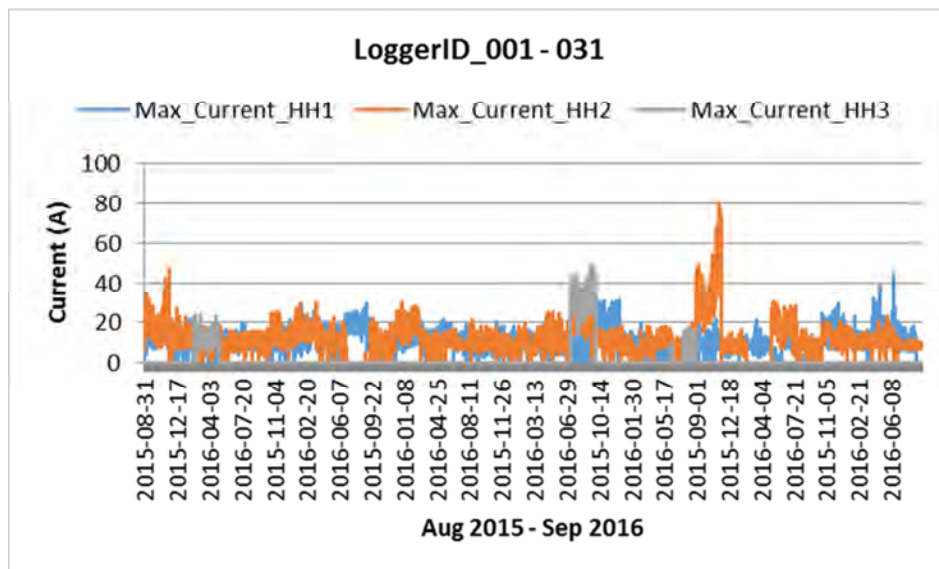


Figure 5-2: Current of all loggers at Mcubakazi for one year

Further analysis was done focusing on just one loggerID\_001 for three households connected on the same loggerID\_001 in Mcubakazi.

Figure 5-3 shows the profile of three households in Mcubakazi for a period of one year, which ran from September 2015 to August 2016. An observation is made on HH3 where the current is close to zero.

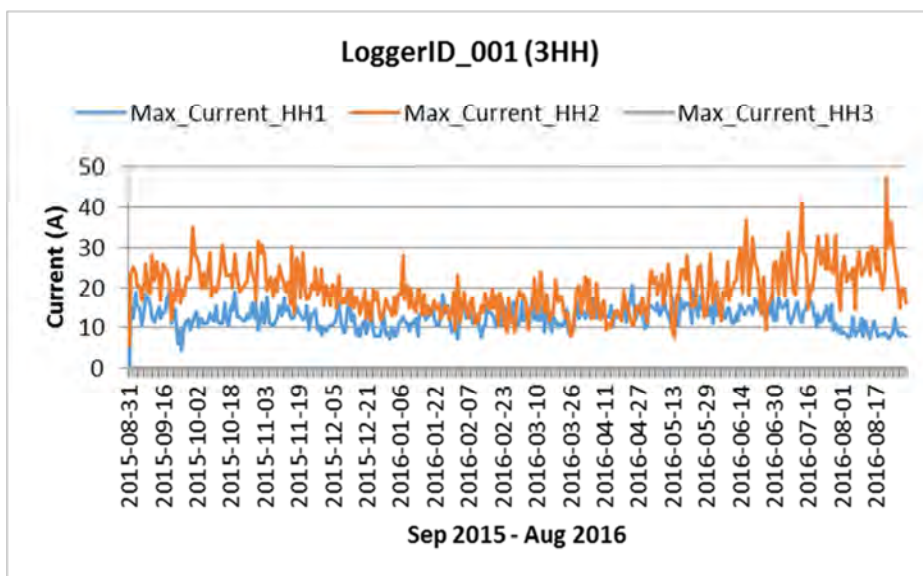


Figure 5-3: Current of one logger at Mcubakazi for one year

Further analysis was done on the same loggerID\_001 for the same period, but which focused on HH1 only. The profile of the analysis is shown in Figure 5-4.

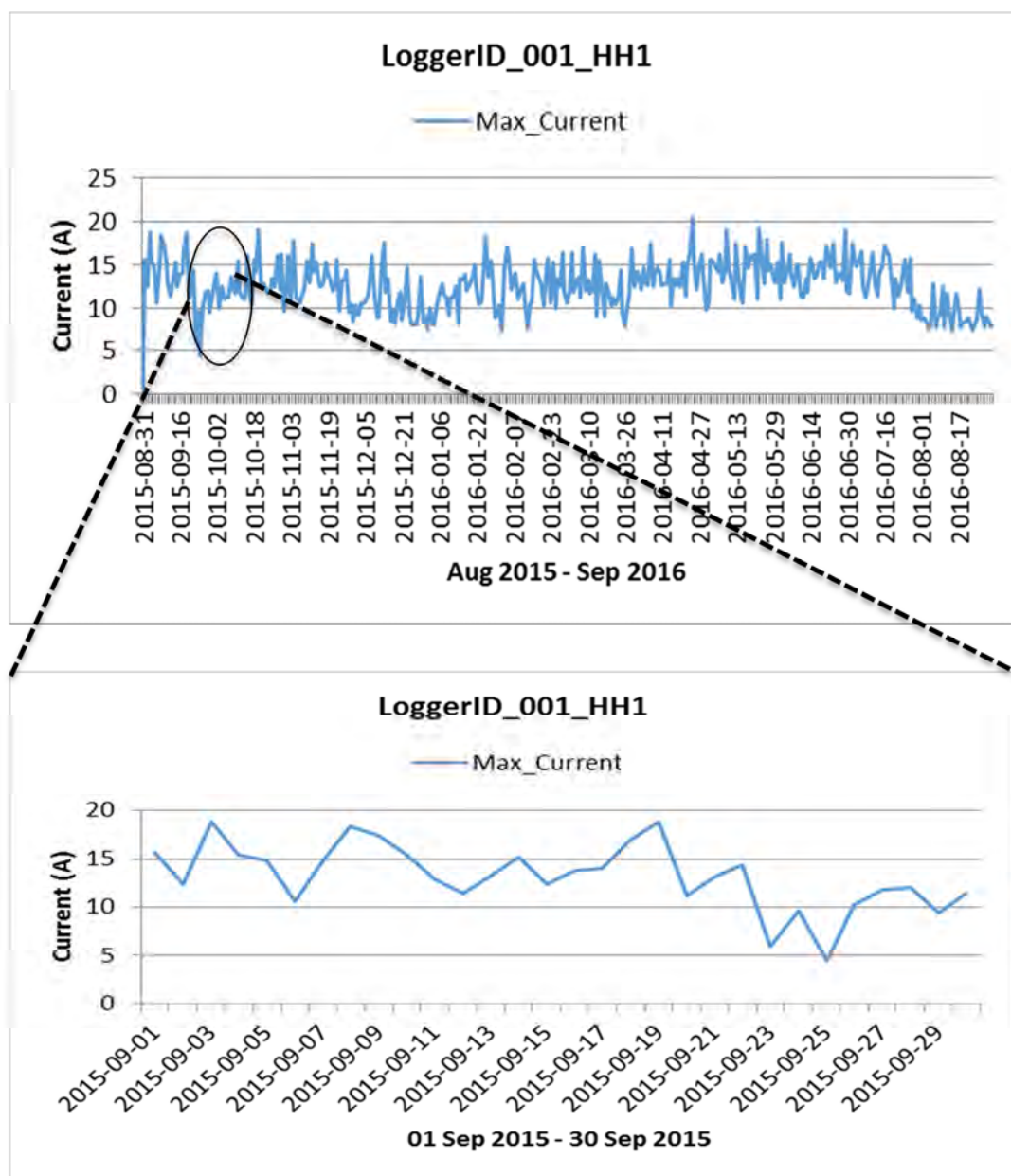


Figure 5-4: Current of one logger one household at Mcubakazi with focus on September 2015 current dip

The dip reaching a maximum current of 5 A (shown in Figure 5-4) around September 2015 and October 2015 can still be seen in Figure 5-4 with a closer zoom in.

Figure 5-5 illustrates the typical 24-hour daily profile showing the morning and evening peaks of one household for a period of one month in September 2015.

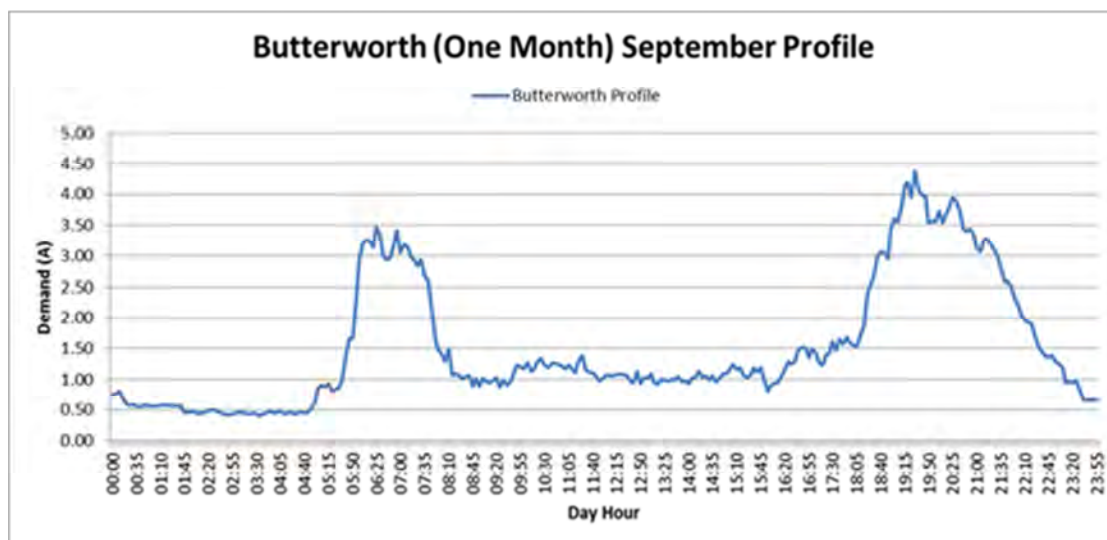


Figure 5-5: 24-hour day profile of one month data

An observation is made on the profile shown in Figure 5-5 where typical morning and evening peaks are seen, although one month data was analysed in this instance. From 05:00 am – 09:00 am it is the morning peak and 06:00 pm – 10:00 pm is the evening peak. This profile coincides with Figure 3-3 in Section 3.3.

### 5.3 DISCUSSION OF RESULTS

For the purpose of this dissertation, the discussion of results is limited to the Mcubakazi and Matshana sites [38]. These results are in conjunction with the usage of probabilistic load model and the Herman-Beta method to calculate the design parameters and ADMD as well as the socio-demographic survey.

The results are from the socio-demographic survey and the meter data. Upon completion of the survey on-site, the forms were captured for analysis and cross-referenced with the previous year for statistical purposes – repeatability and credibility of information – and for modelling purposes.

## MCUBAKAZI<sup>9</sup>

The results of the socio-demographics for Mcubakazi are summarised as follows:

- Most of the households have a 20 A supply.
- Houses are mostly modern style, having tin roofs and block or brick walls as shown in Figure 5-6 and Figure 5-7.
- The built area of houses is in the region of 65 m<sup>2</sup>.
- Most consumers get water from taps in their yards.
- The average gross income is about R7 100 per household per month in a poorly serviced area with gravel roads. The income of the household reflects the purchasing power, which determines the number and type of appliances used.
- There is approximately 47% hotplate ownership and 86% fridge or fridge-freezer ownership.
- The average reported time with electricity is about 11 years. Estimated consumption is about 330.4 kWh per household per month.



Figure 5-6: Photo showing street and type of houses

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<sup>9</sup> Mcubakazi is a township just outside Butterworth in the Eastern Cape Province

Although Figure 5-6 and Figure 5-7 show streets with no tar roads, some roads were being tarred during the research process.



Figure 5-7: Photo showing slightly bigger houses in Mcubakazi

These results were then linked with meter data and the following profile shown in Figure 5-8 was achieved. The profile shows weekday and weekend profiles with average load current of 4 A during winter season.

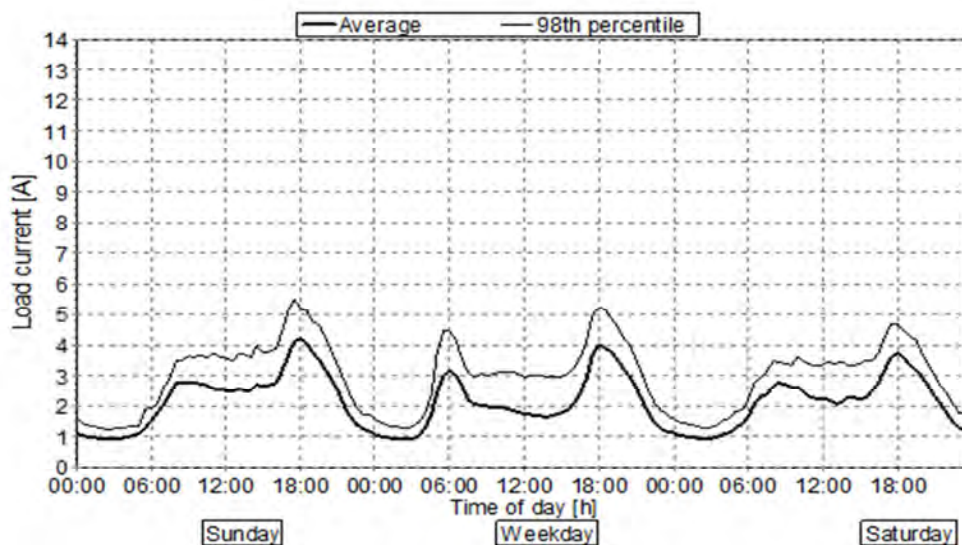


Figure 5-8: Characteristic profile of Mcubakazi

The morning peak of weekend is slightly shorter and flat, which shows that electricity usage continues until midday because family members are at home. The weekday peak is at 06:00 and very sharp.

Figure 5-9 shows the range of current as a function of the number of households. More than 78% of the households are below 7 A electricity usage; these results are critical for network planning. This implies that more than 78% of the households do not have 150 litre geysers as the usage of such a geyser is 13 A. How then to design and plan the network for future? Will the *status quo* remain or change sooner because of economic conditions?

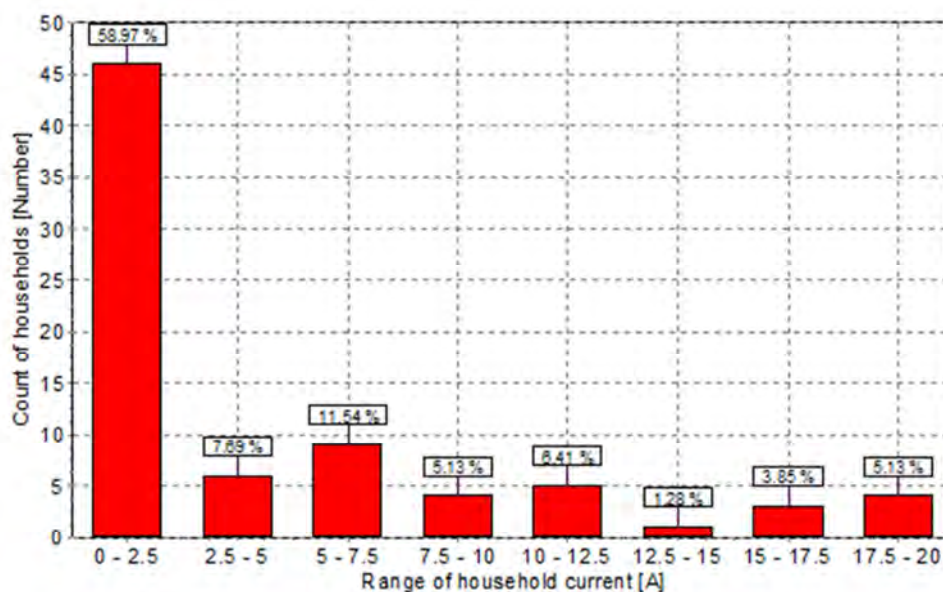


Figure 5-9: Current range of number of households in Mcubakazi

These results were then translated to calculate the ADMD using the design parameters as discussed in Section 3.3. The ADMDs were then calculated for Mcubakazi. This information is used for the purpose of network planning and load forecasting.

## **MATSHANA<sup>10</sup>**

The results of the socio-demographics for Matshana are summarised as follows:

- The households have a 60 A supply.
- Houses are mostly modern style, having tin roofs and block or brick walls as shown in Figure 5-10 and Figure 5-11.
- The built area of houses is in the region of 66 m<sup>2</sup>.
- Most consumers get water from taps in their yards.
- The average gross income is about R2 600 per household per month in a poorly serviced area with gravel roads. The income of the household reflects the purchasing power, which determines the number and type of appliances used.
- There is approximately 39% hotplate ownership and 79% fridge or fridge-freezer ownership.
- The average reported time with electricity is about 13 years. Estimated consumption is about 465 kWh per household per month.



*Figure 5-10: Photo showing area of Matshana, streets and type of houses*

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<sup>10</sup> Matshana is the rural area near Empangeni in the KwaZulu-Natal Province



Figure 5-11: Photo showing rural setup of Matshana

These results were then linked with meter data and the following profile shown in Figure 5-12 was achieved. The profile shows weekday and weekend profiles with average load current of 6 A during the winter season.

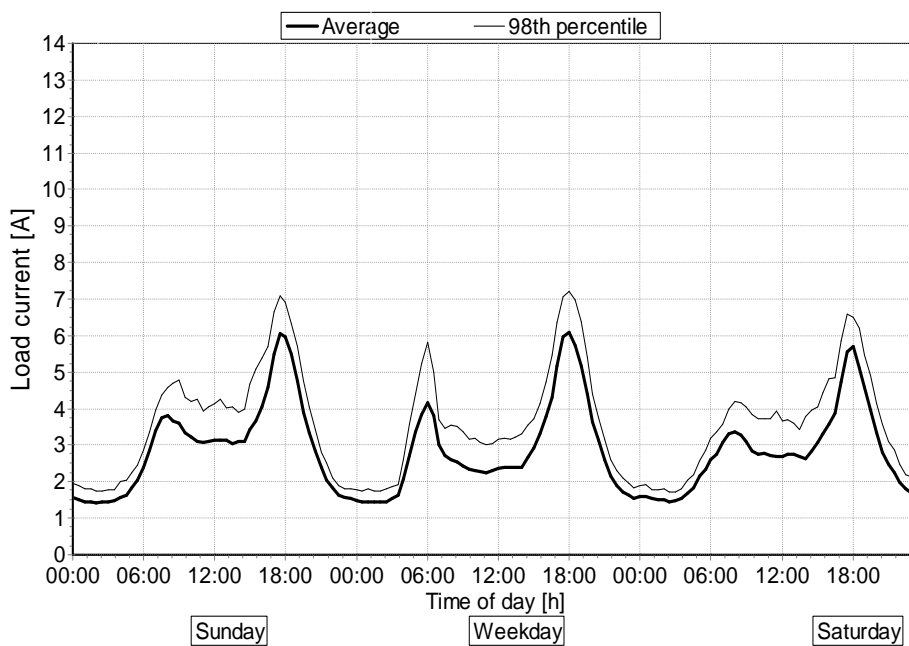


Figure 5-12: Characteristic profile of Matshana

The morning peak of Saturday is slightly shorter and flat, which shows that few customers use electricity in the morning whereas the weekday peak is at 06:00 and very sharp.

Figure 5-13 shows the range of current as a function of number of households. More than 70% of the households are below 7 A electricity usage; these results are critical for network planning. This implies that more than 70% of the households do not have 150 litre geysers as the usage of the geyser is 13 A. How then to design and plan the network for future? Will the *status quo* remain or change sooner because of economic conditions?

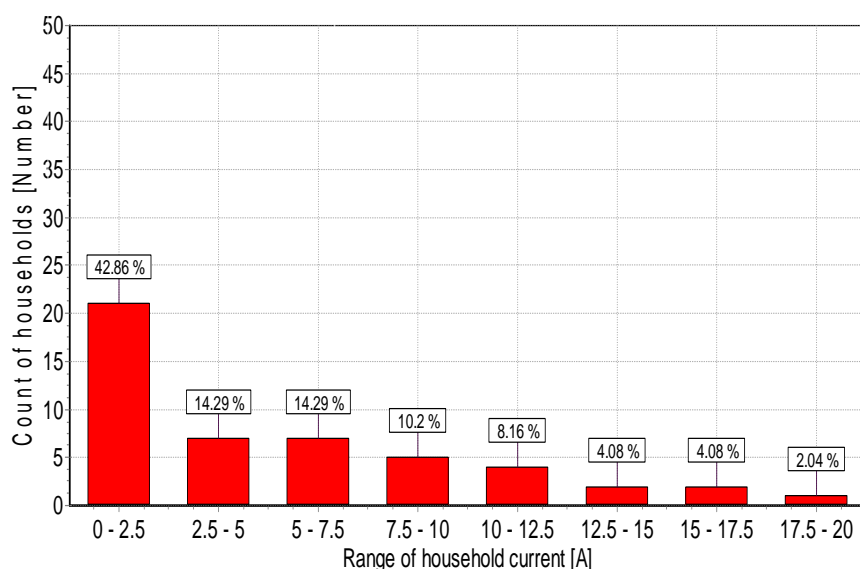


Figure 5-13: Current range of number of households in Matshana

These results were then translated to calculate the ADMD using the design parameters as discussed in Section 3.3. The ADMDs were then calculated for Matshana for a period of five years. This information is used for the purpose of network planning and load forecasting.

### ADMD FOR MCUBAKAZI AND MATSHANA

Table 5-1 provides the ADMDs for the two sites. Although the intent is to compare ADMDs for the past five years, Mcubakazi was sampled in 2011, hence only one ADMD is provided in Table 5-1. One can see the fluctuation of the ADMD in five years for Matshana, which raises questions of what causes this fluctuation?

*Table 5-1: Comparison of ADMD for five years in succession*

Year	Mcubakazi	Matshana
<b>2008</b>	0	1.52
<b>2009</b>	0	1.22
<b>2010</b>	0	1.04
<b>2011</b>	0	1.78
<b>2012</b>	1.38	1.54

The ADMDs for the two sites shown in Table 5-1 are also shown in Table 5-2 with other sites. The mean, standard deviation and the design parameters are shown as well.

The design parameters and the ADMDs for sampled sites have been calculated successfully, and peak loading can be clearly isolated as provided in Table 5-2. These results are critical for network expansion and planning. By multiplying the estimated load with the ADMD, a planner would be able to have a more accurate loading (transformer sizing) value that would even cater for future growth.

Table 5-2: Results per site showing mean, standard deviation, design parameters and ADMD per site

Site	Peak no.	Total [A]	N	Mean [A]	Standard deviation [A]	Error [A]	Alpha	Beta	ADMD [kVA]
Mcubakazi	1	511.2	85	6.01	8.18	1.46	0.43	5.23	1.38
Ga-Luka	1	612.2	66	9.28	8.44	1.71	0.95	7.27	2.13
GanKoane	1	320.8	70	4.58	4.81	0.95	0.80	13.11	1.05
Hankey	1	329.2	67	4.91	5.45	1.10	0.70	10.71	1.13
Matshana	1	382.2	57	6.71	8.18	1.78	0.53	5.82	1.54
Matsulu	1	348.2	60	5.80	5.60	1.19	0.92	11.79	1.33
Seloshesa	1	700.2	85	8.24	6.48	1.16	1.35	11.73	1.89
Vlaklaagte	1	368.6	79	4.67	4.60	0.85	0.91	14.68	1.07
Watville	1	709.2	60	11.82	7.99	1.70	1.72	9.92	2.72

Where:

Peak number: Highest number of peak days, in this case, only one peak day is used

N: Total number of customers per site

Alpha and beta: The design parameters calculated (refer to Section 3.3) using the mean, standard deviation and the size of the circuit breaker.

An observation is made about the sites that are more rural and/or where there is more poverty with an ADMD less than 1.6 kVA. However, this observation should be made with caution as these sites have also shown signs of economic growth manifested in the type of houses recently built.

The large differences in ADMD values for different townships were as a result of low household income resulting in other communities not affording certain electrical appliances such as electric geysers.

## **5.4 CONCLUSIONS**

It is observed that the significance and relevance of understanding the load can be summarised as follows:

- Both under- and overdesigning delivery systems carry a cost penalty; the design parameters have played a significant role in the design of the residential network load using the formula in Section 3.3.
- These research results have demonstrated that socio-demographic parameters can be used to estimate the level of the peak demand. The information gathered during the socio-demographic survey include household income, type of appliances owned, size of house, number of people staying in the house and most importantly, availability of the geyser. These are important variables that influence electricity usage.
- Average daily demand (such as consumption) may be used to estimate the level of the peak demand.
- These results have also provided a description of the nature of the peak demand. The work therefore enables a reduction in error when sizing systems.

Through the results of areas such as Mcubakazi and Matshana, the network designer and planner are better positioned to replicate results to other areas with similar characteristics as Mcubakazi and Matshana.

# CHAPTER 6: CONCLUSIONS AND RECOMMENDATIONS

## 6.1 CONCLUSIONS

There is no doubt that electricity still plays a key role in providing energy to consumers for various purposes ranging from cooling, heating, cooking, preserving food and providing lighting. However, the very network that ensures electricity is distributed to consumers requires attention and care. This is done through proper planning and refurbishment.

The perpetual migration of people from rural to urban areas contributes significantly to the need of network expansion and new electrification projects. With all these requirements, network planners and designers require data to enable cost-effective and efficient designs and planning.

### **Answers to Research Questions**

Through literature survey and data acquisition process, posed research questions in section 1.4 can be answered. The following is the list of research questions and the insight acquired through the research process:

- **What socio-demographics parameters (such as income, appliances, employment and floor space) do the levels of demand, consumption and load profile shape relate most to?**

Household income has been identified as one of the important variable relating to demand and energy consumption. Higher income groups afford appliances such as geysers and swimming pool pumps, these types of appliances add to the increase in consumption, particularly during peak times.

It was observed during socio-demographic survey that lower income groups do not afford electric geysers. The more prevalent appliances in lower income groups are cooking 2-plate stoves and lights. During winter season 2-plate

stoves were used for space heating, hence the geographic area and season also contribute to the shape of the profile.

- **What peak demands, consumption and shape of the load can be expected from different types of community?**

Figure 3-3 in section 3 shows two different profiles of two different income groups, the living standard measure (LSM) is typical LSM 1-to-6. Table 5-2 shows different areas with peaking days. These results vary from one community to another and the reason is mainly income and number of years electrified. In areas such as Wattville and Ga-Luka, there was suspicion of electricity theft (that was not the focus of this study) and that also contribute to high consumption and peak demand.

The probabilistic model and the design parameters were based on the conditions of lower end consumers in terms of financial income. Hence, income and number of years electrified were the key variables during this research. Many local researchers in the field of load modelling concur that in this segment of the lower income group, power factor is unity because of resistive appliances. However, with the penetration of other electronic appliances, it is concluded that the inductive and capacitive loads be modelled locally.

- **How big is the influence of external factors on the levels of demand, consumption and load profile shape?**

The influence of external factors is significantly big for consideration during network design and planning. Typical examples are the weather conditions (temperature) and the economic conditions reflected in the elasticity of tariffs.

- **What are the international trends and lessons learnt?**

Based on the results and the sentiments internationally, it is concluded that the probabilistic model is the preferred model for network design and planning.

### **Further Concluding Remarks**

The data gathering process and development of load models become critical for a utility. These processes have progressed very well in South Africa with the utility playing a leading role. This is important for a developing country as it reduces uncertainties in distribution network planning and design.

From the literature review conducted there are observable benefits by understanding the load and customer behaviour. It is therefore imperative to not only gather metering data, but also data on socio-demographics and ensure linkage of these datasets. It is therefore concluded that this aspect of the research was achieved successfully.

The analysis of customer loads and load estimation is a traditional area of electricity distribution technology. Modern computers and load research data collection techniques and analyses have exposed new sources of information and modelling techniques.

Lastly, from the results above a conclusion is made that further investigation is required to understand what causes the ADMD to fluctuate in time.

## **6.2 RECOMMENDATIONS**

There is a need for future work to further enhance developed load models and statistical techniques. This is necessitated by the growing and complex residential sector. The following recommendations are made for future considerations:

- Urgency to revise and update the design parameters and ADMD, which is necessitated by the expected growth and development in rural and township areas.
- The inductive and capacitive loads in the residential sector (appliance penetration in the market) be modelled even in the lower income group.
- Theft and illegal connection, in terms of “future customers” and also investigation of the impact of “disruptive technologies” (rooftop photovoltaic, embedded generation, renewables, etc.) on network planning.

- Assessment of network performance in an ever-changing environment, i.e. economic conditions, political and social factors.
- With new developments in the residential area and the change from residential houses to commercial properties, it is envisaged that the design parameters would be revised and updated.
- It is envisaged that this research work will continue in future. With this in mind, it is important to stay abreast with the fast advancement of metering technology and communication platforms such as GPRS. IT infrastructure plays a crucial role in ensuring credible and prompt results.

This research work is critical to be taken forward to manage and plan distribution networks, but also is useful information for smart homes initiatives.

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## ANNEXURES A: GOOD DATA RETURNED IN 2013



*Figure A-1: Summary of good data returned from all groups*

In 2013, the total number of sites returning good data ranged from 600 to 800 channels, which are the number of households connected per logger per site. In 2013, the performance of loggers was satisfactorily excellent.

This indeed attests to the success of migrating from old logger technology to new technology. This good data return was also translated to financial savings as attending faults on-site was significantly reduced and therefore traveling cost subsequently reduced.

## ANNEXURES B: DATA SNAPSHOT OF MATSHANA

Logger ID	DATE	HOURL	IN	UN	Hz	V	A	kVA	kW	V	A	kVA	kW
ERID-000MTS001	2015/06/12	0005		5 KW	600	2657.04	0	0.03	0.02	2656.92	4.92	1.56	1.38
ERID-000MTS001	2015/06/12	0010		5 KW	599.16	2631	0	0.03	0.02	2630.88	4.32	1.88	1.74
ERID-000MTS001	2015/06/12	0015		5 KW	599.16	2657.28	0.12	0.06	0.04	2657.16	2.64	0.96	0.73
ERID-000MTS001	2015/06/12	0020		5 KW	599.88	2671.08	0.24	0.12	0.08	2670.96	5.28	1.81	1.7
ERID-000MTS001	2015/06/12	0025		5 KW	600.12	2698.08	0.24	0.12	0.08	2697.96	3.6	1.66	1.54
ERID-000MTS001	2015/06/12	0030		5 KW	599.88	2709.96	0.24	0.11	0.08	2709.84	2.4	0.91	0.73
ERID-000MTS001	2015/06/12	0035		5 KW	598.8	2686.92	0.12	0.07	0.04	2686.8	5.04	1.68	1.6
ERID-000MTS001	2015/06/12	0040		5 KW	598.44	2705.52	0	0.03	0.02	2705.28	3.48	1.64	1.56
ERID-000MTS001	2015/06/12	0045		5 KW	598.68	2717.64	0	0.02	0.02	2717.52	2.28	0.81	0.67
ERID-000MTS001	2015/06/12	0050		5 KW	599.64	2709.48	0	0.03	0.02	2709.36	4.8	1.6	1.51
ERID-000MTS001	2015/06/12	0055		5 KW	600.48	2710.8	0	0.03	0.02	2710.68	4.2	1.94	1.83
ERID-000MTS001	2015/06/12	0100		5 KW	600.36	2719.32	0	0.03	0.02	2719.2	2.64	0.97	0.78
ERID-000MTS001	2015/06/12	0105		5 KW	599.76	2694.72	0.24	0.08	0.05	2694.6	4.92	1.6	1.46
ERID-000MTS001	2015/06/12	0110		5 KW	599.52	2694.6	0.24	0.12	0.09	2694.48	4.2	1.91	1.8
ERID-000MTS001	2015/06/12	0115		5 KW	598.68	2710.56	0.24	0.12	0.08	2710.56	2.64	0.97	0.77
ERID-000MTS001	2015/06/12	0120		5 KW	599.52	2696.04	0.24	0.1	0.07	2695.92	4.92	1.62	1.52
ERID-000MTS001	2015/06/12	0125		5 KW	600	2710.56	0	0.03	0.02	2710.44	3.48	1.65	1.58
ERID-000MTS001	2015/06/12	0130		5 KW	601.32	2720.52	0	0.03	0.02	2720.4	2.4	0.91	0.75
ERID-000MTS001	2015/06/12	0135		5 KW	600.72	2677.92	0	0.03	0.01	2677.8	5.28	1.79	1.71
ERID-000MTS001	2015/06/12	0140		5 KW	600.36	2692.8	0	0.03	0.02	2692.68	3.24	1.52	1.41
ERID-000MTS001	2015/06/12	0145		5 KW	599.16	2694.72	0	0.02	0.02	2694.6	2.4	0.88	0.73
ERID-000MTS001	2015/06/12	0150		5 KW	599.52	2664.96	0	0.03	0.02	2664.84	5.52	2.1	2.04
ERID-000MTS001	2015/06/12	0155		5 KW	599.88	2683.44	0.24	0.12	0.09	2683.32	2.88	1.21	1.08
ERID-000MTS001	2015/06/12	0200		5 KW	600.12	2684.76	0.24	0.12	0.08	2684.64	3.24	1.14	0.97
ERID-000MTS001	2015/06/12	0205		5 KW	600.6	2665.44	0.24	0.12	0.08	2665.32	6.12	2.45	2.37
ERID-000MTS001	2015/06/12	0210		5 KW	600.6	2691.48	0.12	0.08	0.05	2691.36	3	1.14	0.98
ERID-000MTS001	2015/06/12	0215		5 KW	599.64	2676.36	0	0.03	0.02	2676.24	3.72	1.15	1.03
ERID-000MTS001	2015/06/12	0220		5 KW	599.4	2656.32	0	0.03	0.02	2656.2	5.76	2.21	2.16
ERID-000MTS001	2015/06/12	0225		5 KW	600.24	2686.32	0	0.02	0.02	2686.2	3	1.06	0.89
ERID-000MTS001	2015/06/12	0230		5 KW	600.84	2684.4	0	0.03	0.02	2684.28	4.08	1.25	1.15
ERID-000MTS001	2015/06/12	0235		5 KW	600.6	2689.2	0	0.03	0.02	2689.08	4.2	1.91	1.84
ERID-000MTS001	2015/06/12	0240		5 KW	600.12	2706.12	0.12	0.04	0.02	2706	2.4	0.85	0.73
ERID-000MTS001	2015/06/12	0245		5 KW	599.76	2683.8	0.24	0.12	0.09	2683.68	4.92	1.64	1.55
ERID-000MTS001	2015/06/12	0250		5 KW	599.52	2705.52	0.24	0.12	0.08	2705.4	3.24	1.53	1.44
ERID-000MTS001	2015/06/12	0255		5 KW	599.16	2708.04	0.24	0.12	0.08	2707.92	2.28	0.82	0.67
ERID-000MTS001	2015/06/12	0300		5 KW	600.36	2683.92	0.12	0.06	0.05	2683.92	5.16	1.86	1.79
ERID-000MTS001	2015/06/12	0305		5 KW	599.52	2706.36	0	0.03	0.01	2706.24	3.12	1.42	1.32
ERID-000MTS001	2015/06/12	0310		5 KW	599.28	2679.24	0	0.03	0.02	2679.12	3	1.08	0.92
ERID-000MTS001	2015/06/12	0315		5 KW	599.28	2643.48	0	0.03	0.02	2643.36	6.12	2.27	2.17
ERID-000MTS001	2015/06/12	0320		5 KW	599.04	2658	0	0.02	0.02	2657.88	3.84	1.59	1.43
ERID-000MTS001	2015/06/12	0325		5 KW	600.48	2669.04	0	0.03	0.02	2668.92	4.8	1.74	1.59
ERID-000MTS001	2015/06/12	0330		5 KW	601.2	2663.52	0.12	0.05	0.03	2663.4	6.24	2.44	2.36
ERID-000MTS001	2015/06/12	0335		5 KW	600.72	2691.84	0.24	0.12	0.09	2691.72	3.96	1.7	1.59
ERID-000MTS001	2015/06/12	0340		5 KW	600.48	2686.08	0.24	0.12	0.08	2685.96	3.12	1.18	1.04
ERID-000MTS001	2015/06/12	0345		5 KW	600.84	2658.36	0.24	0.12	0.08	2658.24	6.24	2.21	2.13
ERID-000MTS001	2015/06/12	0350		5 KW	601.08	2634.72	0.12	0.05	0.03	2634.6	3.36	1.52	1.4
ERID-000MTS001	2015/06/12	0355		5 KW	600.72	2631.12	0	0.03	0.02	2631	2.04	0.74	0.62
ERID-000MTS001	2015/06/12	0400		5 KW	600.6	2597.04	0	0.02	0.02	2596.92	4.92	1.69	1.64
ERID-000MTS001	2015/06/12	0405		5 KW	600.24	2583.96	0	0.03	0.02	2583.84	4.68	1.72	1.7
ERID-000MTS001	2015/06/12	0410		5 KW	599.52	2574	0	0.03	0.02	2573.88	7.8	2.94	2.92
ERID-000MTS001	2015/06/12	0415		5 KW	599.52	2573.64	0	0.02	0.01	2573.52	11.4	3.96	3.94
ERID-000MTS001	2015/06/12	0420		5 KW	599.52	2593.68	0.12	0.06	0.04	2593.56	9.48	3.71	3.69
ERID-000MTS001	2015/06/12	0425		5 KW	600.6	2605.8	0.24	0.11	0.09	2605.68	8.4	3.03	3.01
ERID-000MTS001	2015/06/12	0430		5 KW	600	2534.76	0.24	0.11	0.08	2534.64	11.4	4.05	4.04
ERID-000MTS001	2015/06/12	0435		5 KW	599.28	2542.68	0.24	0.11	0.07	2542.56	9.24	3.43	3.4
ERID-000MTS001	2015/06/12	0440		5 KW	598.08	2571.72	0.12	0.05	0.04	2571.72	8.4	3.03	3.01
ERID-000MTS001	2015/06/12	0445		5 KW	598.32	2510.28	0	0.03	0.01	2510.16	10.08	3.77	3.75
ERID-000MTS001	2015/06/12	0450		5 KW	598.92	2517.36	0	0.02	0.02	2517.24	6.84	2.49	2.48
ERID-000MTS001	2015/06/12	0455		5 KW	600.36	2540.4	0	0.03	0.02	2540.28	8.16	2.64	2.61
ERID-000MTS001	2015/06/12	0500		5 KW	601.68	2507.88	0	0.02	0.02	2507.76	11.64	4.22	4.21
ERID-000MTS001	2015/06/12	0505		5 KW	600.24	2532.12	0	0.03	0.01	2532	9.36	3.31	3.28
ERID-000MTS001	2015/06/12	0510		5 KW	597.96	2511.72	0.12	0.04	0.03	2511.6	14.04	4.73	4.71
ERID-000MTS001	2015/06/12	0515		5 KW	597.84	2471.64	0.24	0.11	0.09	2471.52	16.08	5.66	5.65
ERID-000MTS001	2015/06/12	0520		5 KW	598.32	2487.48	0.24	0.1	0.07	2487.36	13.08	4.67	4.65
ERID-000MTS001	2015/06/12	0525		5 KW	601.32	2518.2	0.36	0.14	0.13	2518.08	14.04	4.67	4.63
ERID-000MTS001	2015/06/12	0530		5 KW	601.92	2464.44	0.36	0.14	0.12	2464.32	15.6	5.73	5.71
ERID-000MTS001	2015/06/12	0535		5 KW	600.12	2440.2	1.92	0.53	0.53	2440.08	10.32	3.67	3.64
ERID-000MTS001	2015/06/12	0540		5 KW	599.16	2425.8	2.4	0.85	0.84	2425.68	12.48	3.85	3.82
ERID-000MTS001	2015/06/12	0545		5 KW	598.56	2373	2.04	0.74	0.74	2372.88	19.68	6.62	6.6
ERID-000MTS001	2015/06/12	0550		5 KW	597.36	2410.32	2.28	0.77	0.77	2410.2	13.92	4.9	4.89
ERID-000MTS001	2015/06/12	0555		5 KW	598.08	2435.28	2.64	0.85	0.85	2435.16	14.64	4.63	4.61
ERID-000MTS001	2015/06/12	0600		5 KW	600.36	2466.84	1.92	0.76	0.75	2466.72	15.48	5.36	5.31
ERID-000MTS001	2015/06/12	0605		5 KW	601.56	2452.08	0.48	0.11	0.11	2451.96	8.52	3.19	3.14
ERID-000MTS001	2015/06/12	0610		5 KW	601.8	2387.04	0.48	0.16	0.15	2386.92	9.84	2.66	2.63
ERID-000MTS001	2015/06/12	0615		5 KW	600.48	2379.84	0.36	0.16	0.14	2379.72	8.88	3.01	2.99
ERID-000MTS001	2015/06/12	0620		5 KW	598.92	2364.72	0.36	0.14	0.14	2364.6	13.44	4.23	4.21
ERID-000MTS001	2015/06/12	0625		5 KW	599.04	2304.36	0.24	0.1	0.09	2304.24	14.4	4.72	4.71

Figure B-1: Data snapshot of Matshana