A LOAD PROFILE PREDICTION MODEL FOR RESIDENTIAL CONSUMERS IN SOUTH AFRICA

Dr S Heunis and M Dekenah
Demand Intelligence Group: Enerweb

ABSTRACT

A revised model that estimates the load profiles for residential consumers in South Africa was developed and is described in this paper. Through the NRS 034 domestic load research programme a large number of load profiles of residential consumers from various Living Standards Measure (ie LSM) classes were collected. The load profiles are further described by a set of socio demographic indicators which is obtained through a front-door survey. A model that relates the hourly customer load profiles to household income, time electrified and region was developed and the output may be used in various planning activities, e.g. electrification design, network expansion planning, long term load forecasting etc. This analysis covers all data collected to end of 2011. A software implementation of the model is available which allows the user to obtain estimates of hourly profiles for different months given a set of input parameters.

1. INTRODUCTION

Load profiles for residential consumers are required in a range of planning, design and management activities in Eskom. For example, electrification design, master planning and cost-of-supply studies.

Through the NRS 034 Domestic Load Research Project ([1] and subsequent annual reports), where Eskom is one of the main contributors, load and socio-demographic information of households from various income and geographical groups was captured.

Before planners can utilize the 'raw' collected data in their day-to-day tasks, it needs to be:

- Filtered
- Analyzed and Modelled to identify significant variables and quantify the relationships between key variables
- Packaged into a user-friendly decision support tool

This paper details the key technical issues that were involved in the derivation of an hourly load profile model for South African consumers, as implemented in the Distribution PET 2012 computer programme. The analysis was conducted in October 2011.

The hourly load profile model was derived from filtering, analysis and processing of load readings collected over the period 1994-2011 inclusive. 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 [2].

The hourly load model consists of non-linear hourly models for Weekdays, Saturdays and Sundays, for each month of the year, and accounts for differences (where significant) in seasonal consumption, climate, and geographic position (east-west time shift, and north-south daylight hours).

2. DATA SOURCES AND FILTERING OF DATA

2.1 RESIDENTIAL AND SOCIODEMOGRAPHIC DATA

Five minute load profile data and linked socio-demographic was obtained from the National Residential Load Research Project, this comprised of 900 million load readings and 8416 completed socio-demographic questionnaires.

Socio demographic questionnaires were filtered based on field domain and redundancy information in some of the questionnaire fields.

The first step of the load data filtering is to mark the load data using the modified Seleck rules using the GLR software module – LoadMarker [3]. Data is marked per day and an entire day is either included or excluded. For non-profile modelling, this is normally sufficient.

However, for profile modelling the following is required:

- The same customers
- For a number of different time intervals

A trade-off between number of customer (sufficiency) and time intervals covered (bias) is made. The percentage of time with sufficient load data measure is due to both missing and filtered data. In any time period a profile would be included if data (after filtering) was present for more than 75% of the time. This would mean, for any month for a particular day type (e.g. Sunday) and hour, data had to be available for 3 out of the 4 Sundays in the month. All data recorded during public holidays were removed from the model data set.

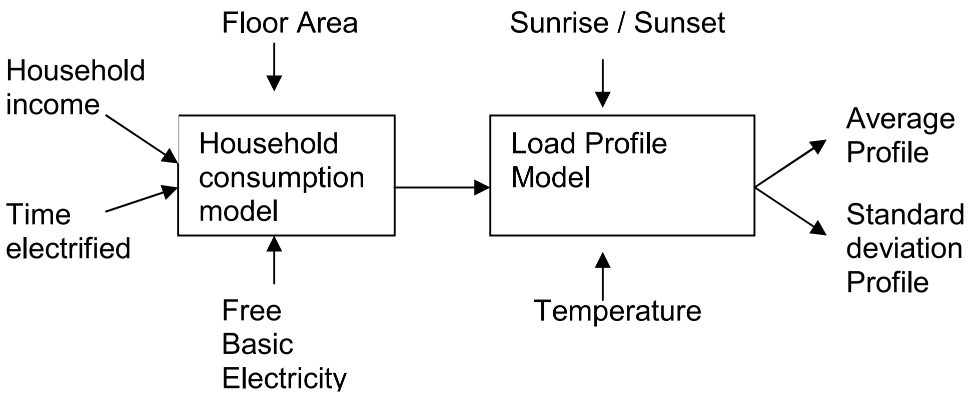


Figure 1: Structure of the load profile model

2.2 OTHER DATA SOURCES

The shape of load profiles is a function of a number of external drivers:

- Time of day, e.g. sun rise, sun set, lunch time
- Temperature
- Rainfall

2.2.1 Sunrise and sunset information

For each Load Research site, the relative amount of sunlight was calculated for each hour using the physical location of the site. This relative amount of sunlight for hour h is calculated as

RSh = 0 if before sunrise or after sunset
= (time since sun rise) if h < 12
= (time before sun set) if h>12

The relative sunlight was calculated for each LR site for each month and each hour.

2.2.2 Temperature and Rainfall

Hourly temperature and monthly rainfall data collected from 24 weather stations throughout South Africa was sourced from the South African Weather Service. Average (temperature per month and per site) and average rainfall (per month and per site) was calculated from this. Data from the closest weather station was taken to represent that at each load research site.

3 ANALYSIS AND MODELING

The load profile prediction model was structured as indicated in Figure 1.

The different components of the models are described in section 3.1 and 3.2.

3.1 HOUSEHOLD CONSUMPTION MODEL

More than 40 different kinds of sociodemographic variables collected from consumers were tested against their associated load, in terms of both statistical significance and usefulness. This included:

- appliance ownership and usage
- cooking habits, usage of alternative fuels, water source
- household member demographics, e.g. age, education, employment etc.
- household income
- connection information , when first connected, circuit breaker size etc.

Many of these variables have a statistical significant relationship with household consumption, however not all can serve as practical predictors. From a causal point of view, only appliances cause consumption, and only if they are operated by consumers, according to their habits.

Appliance ownership is strongly linked to disposable income, which in turn is related to household income. The appliance acquisition - time curve is strongly influenced by household income as first order driver.

The following factors may also influence appliance ownership in some circumstances:

- Household income, expenses and disposable income
- Time since electrification
- Availability and cost of alternative fuels
- Circuit breaker size (load limiting)
- Appliance availability
- Infra-structure (water availability)
- Size of the dwelling (multiple appliance ownership)
- Number of occupants per dwelling

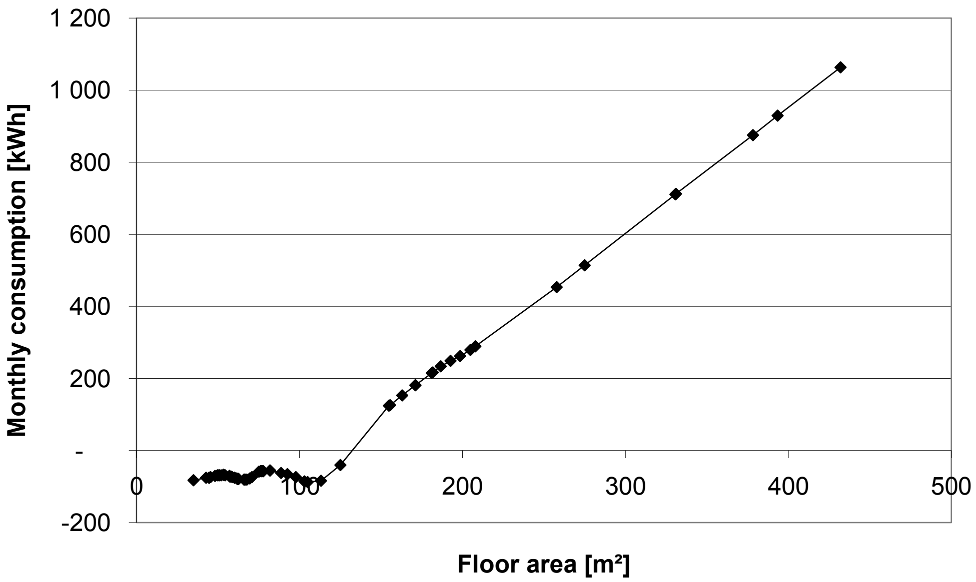


Figure 3: Marginal contribution of Floor Area to Household Consumption

he majority of these circumstances are directly or indirectly driven by the general level of wealth in a community

A Linear model was fitted using household income (adjusted for inflation using CPI) and time since electrification as predictors and seasonal corrected household consumption as response. The model only explained about 80% of the relationship. A non-linear local regression model fitted to the same data showed improved performance: $R^2 = 0.96$ and Standard Error (SE) of 80.1 kWh. This represents an overall improvement in performance over the last 3 years.

3.1.1 Floor Area

For higher income customers, floor area appears to be having a significant effect – this was noticed in households in townhouse complexes where the floor area is relatively small compared to other households with similar income. Figure 3 shows the shape of the estimated marginal contribution of Floor Area to Household Consumption. This relationship is largely unchanged over the last 3 years.

3.1.2 Free Basic Electricity

As part of the impact of basic electricity study [4], a model was derived that estimates the elasticity of household consumers to Free Basic Electricity. This model uses an estimate of the uninfluenced household consumption, to estimate the increase in consumption due to the free units. The measured data points and fitted regression model is shown in Figure 4. No further direct measurements of elasticity have been undertaken over the last 3 years. This model is therefore unchanged.

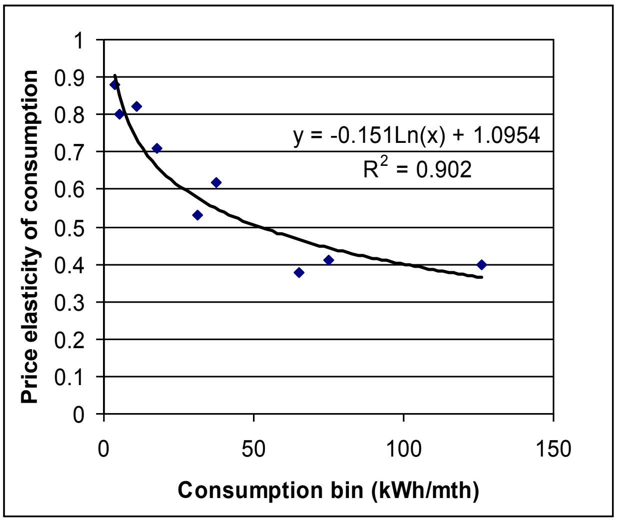


Figure 4: Measured elasticity of residential consumers to the Free Basic Electricity Tariff

3.2 LOAD PROFILE MODEL

The hourly load of a group of households for a particular month and weekday type can be represented as a typical profile (or average profile) and the probable movement from the average (measured as standard deviation).

Two different models were therefore generated, Average profile and Standard deviation of profile, as illustrated in Figure 5.

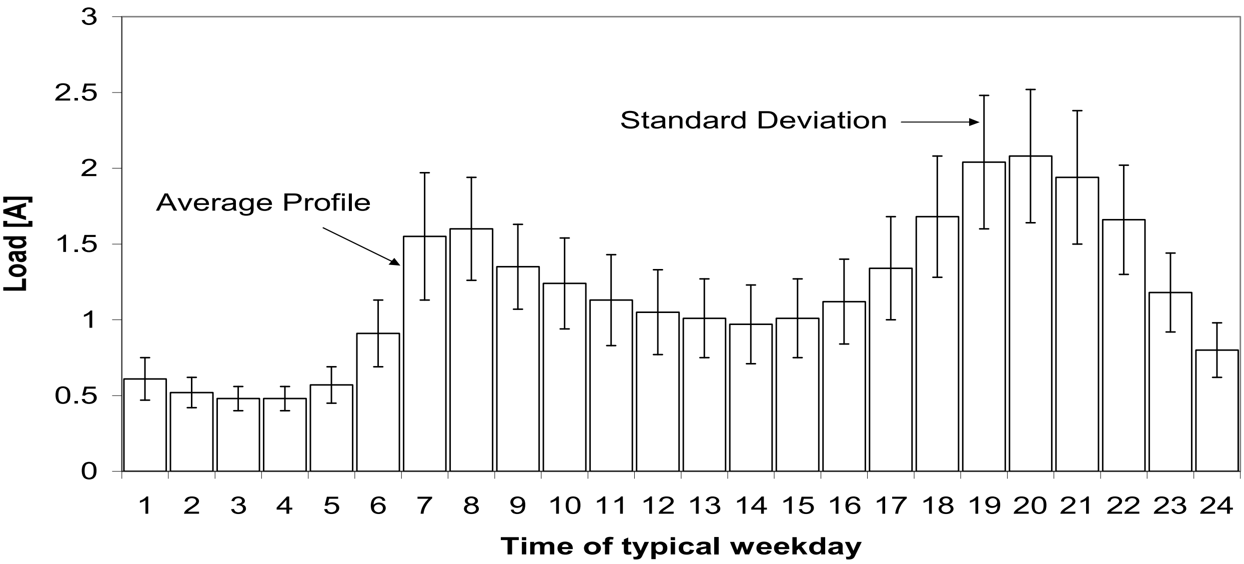


Figure 5: Average profile with standard deviation

3.2.1 Average Load Profile

For each month, weekday type (Weekday, Saturday and Sunday) and hour the significance of household consumption, temperature and relative sunshine as predictors was tested.

The average annual consumption is used as main predictor in conjunction with above factors. The model is a "Generalised Additive Model" (GAM) with local regressed components on Temperature, daylight and average annual consumption where applicable. This means that the model is non-linear and the non-linear components are estimated using local regression.

There are sub-models, describing separate regressions for:

- Consumption class (less than 320kWh/mth and greater than 320kWh/mth).
- Month class (May-August, December-January, February-April + September-November)
- Weekday class (Weekdays, Saturday and Sunday)
- Hour of the day (0-23)

The following sensitivities were noted whilst resolving the regression models:

- Time of day 6 am and 6 pm is significantly affected by sunlight presence or absence, none of the other hours has a significant response.
- Winter months (May – September) are affected by temperature and then most significantly in the medium – high consumption sites
- December and January has distinctly different profile shapes than other months, especially in the higher consumption communities

In all, a total of 432 linear regression models were used to describe the profiles in the prediction space (for profile Mean and profile Standard deviation).

General quality of fit of these profile models is summarised as follows:

- The R^2 is greater than 70% for all models with a mean $R^2 = 90\%$.
- Standard Error (SE) is less than 0.25kVA with a mean SE= 0.08 kVA.

3.2.2 Standard Deviation Profile

The model for standard deviation of the profiles was derived by first normalizing the profiles based on the average profiles. The model therefore uses the mean profile as its main input and is a local regression between the standard deviation per hour and weekday against the mean profile.

The performance of the model for the standard deviation of the profile was $R^2 = 0.87$ and a Standard Error = 0.69 A (or about 150 W per household).

4 PACKAGING – DISTRIBUTION PRE-ELECTRIFICATION TOOL

The model was packaged as part of the Distribution Pre Electrification Tool [2010], a standalone design parameter decision support tool. It allows the user to specify:

- the location of the site of interest,
- the average household income (R0 – R 25 000 per household per month),
- floor area,
- free basic electricity

These input parameters are used to estimate, using the models described in section 3, and graphically display:

- the average consumption per year 1 – 15 after connection,
- after diversity maximum demand per year 1 – 15 after connection,
- Herman-Beta design parameters [6] per year 1 – 15 after connection
- Hourly average and standard deviation profiles, per month, weekday type for each year 1 – 15 after connection

The software allows predicted Consumption, Admd and load profiles to be estimated, viewed and exported using the clipboard, into (for example) Microsoft Excel, to perform further analysis and comparison. Estimates are stated at transformer zone level.

All load parameter estimates are driven by estimates of household income.

Uncertainty in the estimate of this parameter causes uncertainty in the output values.

The load predictions can be risk - adjusted to reflect the uncertainty in the model to cater for the effect of errors in estimating the average income per household per month. The amount of risk adjustment, expressed as probability, needs to be determined.

5 CONCLUSIONS AND FUTURE WORK

A model that estimates load profiles for residential consumers in South Africa was revised with data collected from year 1994 – 2011 inclusive, and is described in this paper.

The model comprises a household consumption model and an hourly electric load profile model.

Both models contain non-linear relationships and are modelled using local regressions. The models have been implemented into the Distribution Pre Electrification Tool (DT PET 2012), a computer programme that allows users to specify features of the target community to estimate the final load profile.

A sample design for the collection of load data from residential consumers in South Africa has been compiled and will be used to collect further data in order to enhance this model and improve its performance. The statistical models in Distribution PET will be updated with the latest information in the next 2 years.

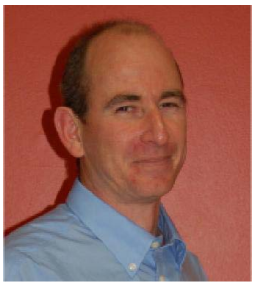
5 ACKNOWLEDGMENTS

This work was funded by Eskom, and directed by the DSM, Energy Efficiency & Customer Research Steering Committee under Amal Khatri, (Activity Leader: Lloyd Setlhogo).

6 REFERENCES

[1] M Dekenah, S Heunis, Load research Studies, Report No. RES/RR/05/27070, Eskom TSI, Oct 2005.
[2] M Dekenah, S Heunis, Manual for DT-Pre Electrification Tool (Distribution PET), March 2010.
[3] Manual for Generic Load Research Database System, Marcus Dekenah Consulting, Sept 2003.
[4] M Dekenah, S Heunis, CT Gaunt, J Cheek, “Technical effects of a basic electricity support tariff for poor consumers”, Report ref. 20031117b md, Marcus Dekenah Consulting, Sept 2009.
[5] Hornik, “The R FAQ”, ISBN 3-900051-08-9, http://CRAN.R-project.org/doc/FAQ/R-FAQ.html
[6] R Herman and JJ Kritzinger, “The statistical description of grouped domestic electrical load currents”, Electric Power Systems Research, vol 27, pp. 43 - 48

7 AUTHORS



Principal Author: Schalk Heunis Holds a PhD in probabilistic modeling of power systems from the University of Stellenbosch (South Africa). He obtained his B.Eng and M.Eng degrees in Electrical Engineering from the University of Pretoria in 1994 and 1998.

In 2003 he joined Enerweb, where his responsibilities included load research, software architecting and system design. During this time, he headed the design team for the implementation of the Virtual Power Station for Eskom.

In 2011 he co-founded House4Hack with the purpose to promote innovation through open hardware and software. House4Hack has been involved and has supported winners of the first and third Gauteng innovation competition, Rorotika innovation to change the world andthe Gada prize for interim personal manufacturing.

His current area of interest is analytics for the internet of things.

Co-author: Marcus Dekenah holds an NHD Elec Eng HC (Cape Technikon, 1983), M. Dip. Tech. Eng. (Cape Technikon, 1987), a BSC Eng (1st Cl hons, UCT, 1991) and MBL II (Unisa, 1996).

Marcus Started his career at the Electricity department at Cape Town City Council involved in a wide range of distribution operations (1980-1988).

From 1991- 1995 Marcus was executing contract research projects in HV testing, Energy management and Load research at Electric Power programme, Division of Energy Technology, CSIR.

In 1996 Marcus formed his own company and has since conducted contract load research both inside and outside South Africa with multi-disciplinary teams of specialists from Industry, private, and the academic sectors.

Marcus has been technical lead for the NRS 034 domestic load research project since 1993.

Marcus is currently assisting the Demand Intelligence Group : Enerweb with the execution of load research.

Presenter: The paper is presented by Mr M. Dekenah.