A load profile prediction model for residential consumers

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This paper describes a model that estimates the load profiles for residential consumers in South Africa. the model was derived using a large number of load profiles of residential consumers from various LSM classes which were collected through the NRS 034 domestic load research programme. 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. 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.

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], 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 utilise the "raw" collected data in their day-to-day tasks, it needs to be:

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

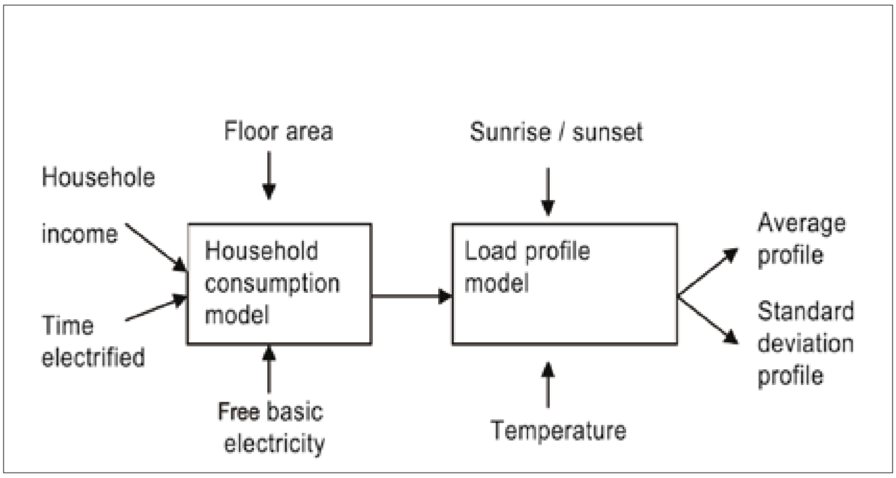

Fig. 1: Structure of the load profile model.

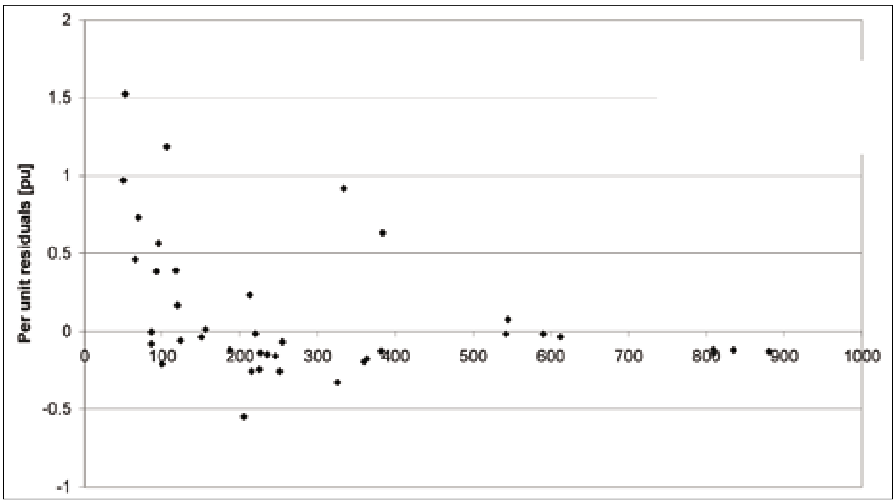

Fig. 2: Per unit residuals of the fitted non-linear model against the various sites where load research data was collected.

Load profile model

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 2005 computer programme. The analysis was conducted over the period 2005 – 2006.

The hourly load profile model was derived from filtering, analysis and processing of 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 [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).

Data sources and filtering of data

Residential and socio-demographic data

Five minute load profile data and linked socio-demographic was obtained from the national residential load research project, which comprised of 618-million load readings and 6190 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 it is required to use same customers over a number of different time intervals

A trade-off between number of customers (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 three out of the four Sundays in the month. All data recorded during public holidays were removed from the model data set.

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

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 hours 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.

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.

Analysis and modeling

The load profile prediction model was structured as indicated in Fig. 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

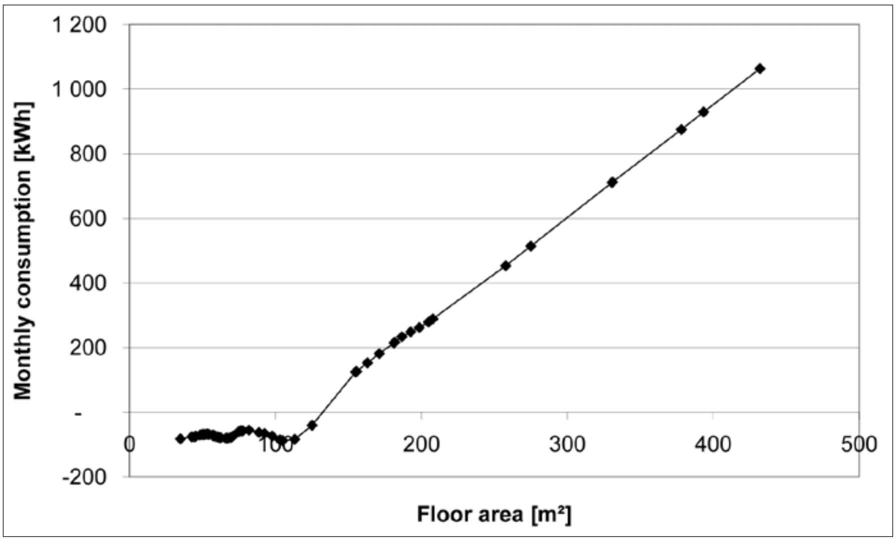

Fig. 3: Marginal contribution of floor area to household consumption.

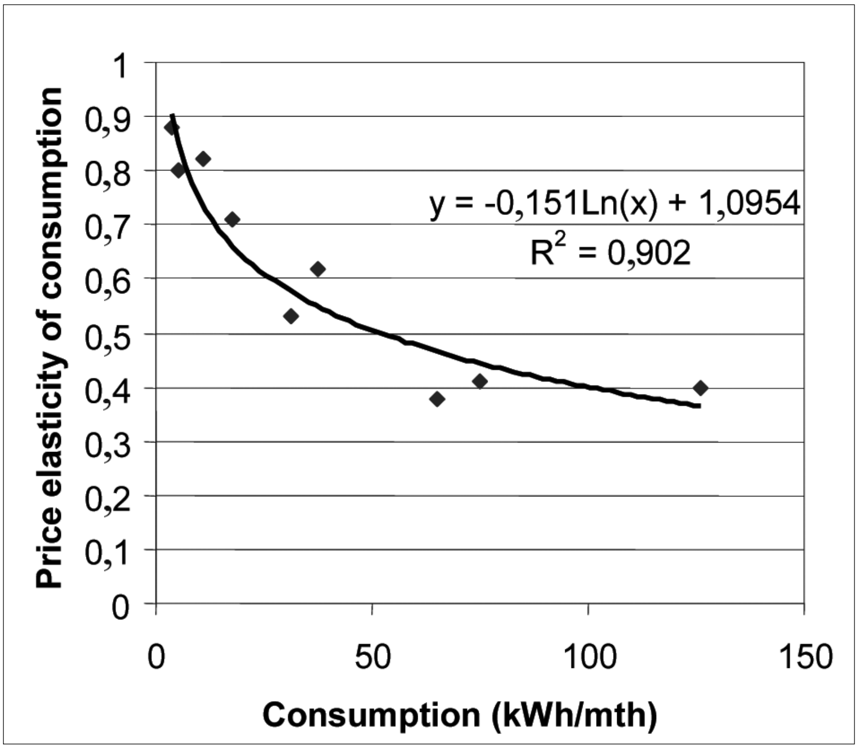

Fig. 4 : Measured elasticity of residential consumers to the free basic electricity tariff.

- Infra structure (water availability)
- Size of the dwelling (multiple appliance ownership)
- Number of occupants per dwelling

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

A model was fitted with household income (adjusted for inflation using CPI) and time since electrification as predictors and seasonal corrected household consumption as response. A non-linear local regression model was fitted using R [5] and has a standard error of 80 kWh and an R^2 of 0,87. Fig. 2 shows the residuals of the fitted non-linear relationship.

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. Fig. 3 shows the shape of the estimated marginal contribution of floor area to household consumption.

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 Fig. 4.

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

Average 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 form of the model for the average profiles is different per hour and per month:

- 06h00 and 18h00 is significantly affected by sunlight presence or absence, none of the other hours has a significant response.
- Winter months (May – September) is 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.

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.

The performance of the model for the typical profile was R^2 = 0,95 and a standard error = 0,54 A (or about 120 W per household).

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).

Packaging – distribution pre-electrification tool

The model was packaged as part of the distribution pre electrification tool [2], a standalone design parameter decision support tool. It allows the user to specify:

- The location of the site she is interested in
- The average household income (R0 – R15 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 one to export the load profiles using the clipboard, into (for example) Microsoft Excel, to perform further analysis and comparison.

For example, Fig. 6 shows a comparison of the average profiles for two consumption groups, R1000 and R10 000 per household per month, for summer (M2) and winter (M6). The higher income group is clearly temperature sensitive and has a very different profile shape compared to the lower income group.

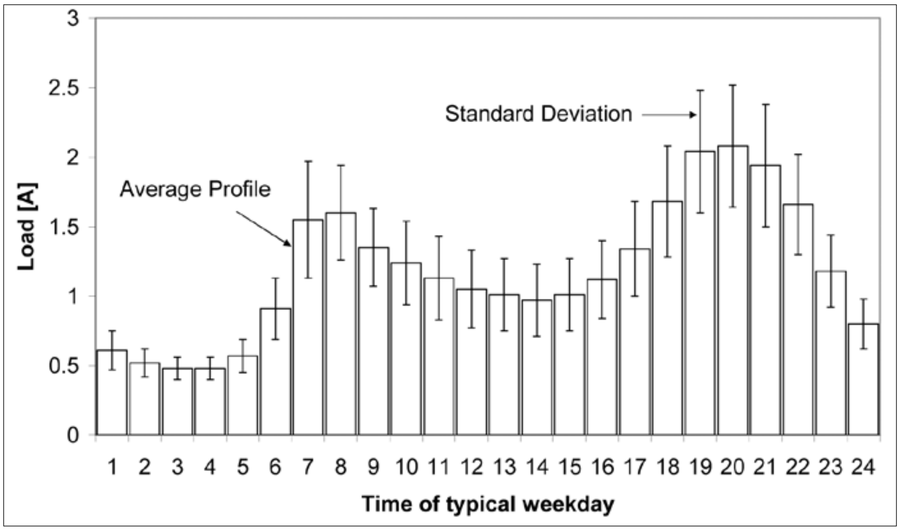

Fig. 5: Average profile and standard deviation profiles.

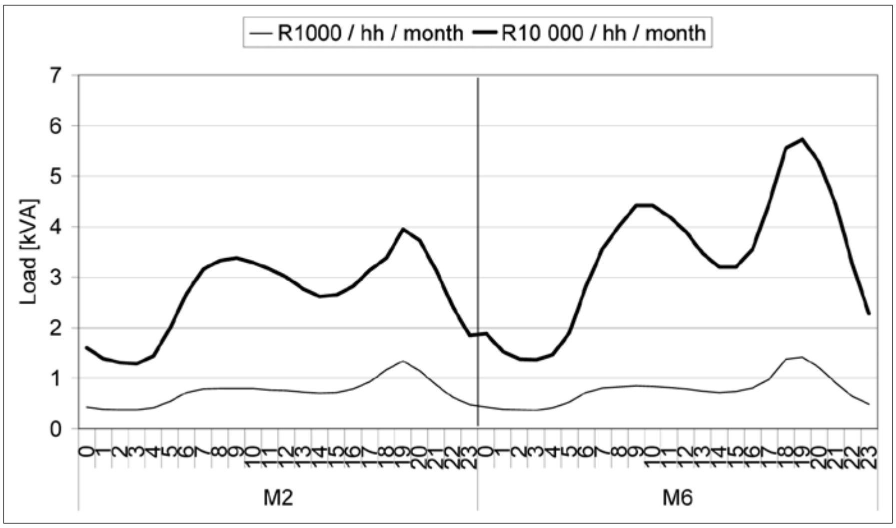

Fig. 6: Average profiles for consumers at R1000 per household per month and R10 000 per household per month. The difference between the summer (M2) and winter (M6) profiles is shown.

Conclusion and future work

A model that estimates the load profiles for residential consumers in South Africa was developed and is described in this paper. The model comprises a household consumption model and an hourly load profile model.

Both models contain non-linear relationships and are modelled using local regression models. The models were implemented into the distribution pre electrification tool (Distribution PET), a computer programe that allows users to specify features of the target community to estimate the final load profile.

The model was developed using data collected from 1994 – 2004, since then additional sites were identified and data collected. The statistical models in distribution PET are in the process of being updated with this information.

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