Method for Rural Load Estimations
– a case study in Tanzania

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Abstract

This article is based on a Master Thesis in Energy Economics and Planning[1] at Lund Institute of Technology. The thesis was based on a minor field study in Tanzania. The aim of the study was to develop a practical and simple algorithm for rural load classification and estimation.

1 Introduction

The expansion of rural electrification in many developing countries is very slow as a result of many factors. E.g. (a) the high costs associated with rural electrification, lack of appropriate distribution standards for rural networks, (b) lack of appropriate methodology for planning and design and (c) operational disturbances as e.g. theft and vandalism.

In Sub-Sahara Africa about 400 million people are still not connected to electric power grids and in e.g. Tanzania only as few as 2% of the rural population have access to electricity.

Load estimation is central when planning electrification systems in urban, peri-urban and rural areas. It sets the guidelines not only for the supply system design and its viability, but also gives an indication of what socio-economic benefits electrification would generate.

1.1 Background

To estimate the total load in terms of peak power demand, average power and energy consumed, aggregation of "predicted" consumption is done. Normally the use of "ad-hoc" coincidence factors, simultaneous load factors, After Diversity Maximum Demand (ADMD) factors etc. are then applied and multiple loads are typically linearly added.

The magnitude of an individual household peak is typically a function of how many appliances there are and the chance that any number of appliances will be in use at a particular time. However, load surveys shows that consumers in low-income rural areas rarely develop more than 12A of load current and different studies indicate maximum average power usage between 200W to 500W[2].

The power peak for a large group of customers (ADMD) is the simultaneous Maximum Demand and is normally calculated as Maximum Demand/N, where N is the number of customers. This value generally decreases to an approximate constant value for 1000 and more customers. However, at small groups the ADMD can significantly differ from site to site. However, to allow for full diversity the number of similar customers should typically be over 100.

Another commonly used method to estimate the peak power demand from a group of customers is the "Velander formula". This formula relates the yearly energy demand (E) to a peak power value using a non-linear relationship as:

$$P_{\max} \; ? \; k_1 \, ?E \; ? \; k_2 \, ?\sqrt{E} \, ,$$

k_1 and k_2 are chosen empirical constants.

However, comparing the output from using the Velander formula for low-income households it often shows the peak power is overestimated by up to as much as 500%.

The commonly used methods for load estimation in rural settings have therefore significant drawbacks, as they don't differ among household users, productive use of electricity (industrial, semi-industrial and commercial), and night loads (street lighting, water pumping etc.).

Central to both the ADMD method and the Velander formula used to estimate peak, average power and energy consumption, is how the load

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[1] Method for Rural Load Estimations, Master Thesis work; Henrik Blennow, LTH, October 2004

[2] Characterization of Power System Loads in Rural Uganda; Frances Sprei, Master Thesis work, LTH, November 2002

aggregation is done. While the ADMD and Velander formula works for rather big groups (e.g. > 1000 consumers), almost no good models exist for smaller load groups (e.g. < 500 consumers).

While the currently applied methods for load estimation is based on connection factors, simultaneous factors, Velander coefficients etc., there is further a lack of transparency and large prediction errors may occur. The most obvious result is that peak power is heavily overestimated and this in turn results in over dimensioned and too costly systems, and the "status quo" in high-cost rural electrification thus remains.

1.2 Objectives of the study

The objective of the study was to develop a practical and simple algorithm for rural load classification and estimation, applicable to small sample sets (< 500 customers), based on socio-economic data and objective/transparent information on loads and load patterns.

1.3 Applied work methodology

The study was oriented along (a) data collection, (b) synthesis, (c) conceptual modelling and (d) preliminary model analysis and comparison with existing methods. The work includes field studies of electricity consumption in rural Tanzania, followed by theoretical analysis and discussions of a possible methodology applicable to rural load estimations.

2 Field study

The collected data was gathered by a number of field surveys, interviews, observations and practical measurements from two non-electrified and five electrified rural villages in Tanzania. Most of the raw data were gathered in Mkuza village, located 10 kilometres west of Dar es Salaam.

The data were extensively used as a basis for classifications and for designing the estimation algorithm. The field studies included measurements of electric appliance consumption levels and to some extent corresponding usage patterns.

2.1 The TANESCO load estimation model[3]

The commonly applied method for load estimation in Tanzania is that each load is grouped into a category load like e.g. small house, bar, maize mill, street lighting, mosque etc. Each load is described by a maximum or average power. Loads are then divided into day, evening and night time-frames and multiplied with its actual numbers. Coincidence factors may be applied and the aggregated load is found as the total sum of all categories.

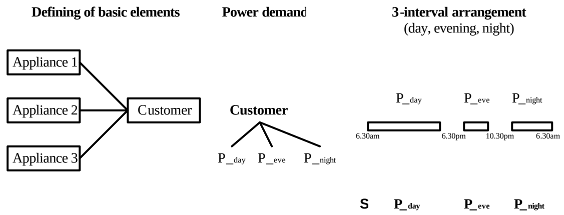

Figure 2.1 *TANESCO load estimation method.*

3 Conceptual algorithm design

In order to allow for a new simplified and more transparent load estimation method, adjusted to small rural loads, the suggested algorithm should (1) maintain raw data in unaltered format throughout the computations and (2) allow for different aggregation formulas.

In contrast to the commonly used TANESCO model, ultimately dividing the consumption over time periods like evening, night and day only, the proposed algorithm instead distribute power consumption over the entire 24 h, related to its base classification on appliance rather than customer type. Compare figure 2.1 above and figure 3.1 below.

The distribution of loads can in this case better handle intermittent (stochastic) loads as e.g. pumps, maize mills, welding equipment and other industrial/semi-industrial loads.

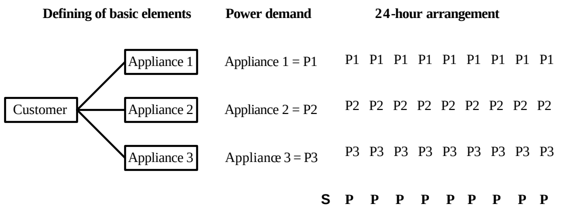

Figure 3.1 *Proposed algorithm structure*

3.1 Classification of loads

The algorithm initially distinguishes between the load types (a) deterministic (b) stochastic and (c) critic-stochastic loads. The deterministic loads are those with a known and predefined usage pattern, like e.g. day and night lighting. It can also be some industrial processes with a constant or well known power profile. The stochastic loads are those loads which are known to size but unknown in time. Refrigerators, water supply pumps, welding equipment, maize mills, stone quarries belong to this category. Critic-stochastic loads are a sub-group of stochastic loads, but whose sizes make them of special interest. A refrigerator of 200 W is not a critic-stochastic load, while a 10 kW maize mill in a network of a peak power demand of 300 kW is.

[3] "Participatatory Appraisal of Socio-Economic Aspects in Wino ward, Tanzania", Swedish International Development Cooperation Agency *Sida*, Daati, Mwungi, Wino Development Association, 2003

3.2 Forming a consumption matrix

For each appliance the power demand is recorded and for deterministic loads distributed over the 24h period of concern as known. This also allow for weekly and seasonal model variations (e.g. less pumping in rainy season, no industrial loads on Sundays etc.)

However, for stochastic loads the distribution over the day is somewhat more complex, as only energy and peak power typically is at hand. A number of suggestions have been tested, but in principle two methods emerged during the work as simple and straight forward.

The simplest method imp lies that the peak power demand is distributed for each time interval, but that geometric addition is applied when calculating the aggregated stochastic load. The other method, a little more computational oriented, uses a Monte Carlo approach, where operation of individual stochastic loads are simulated using a random number generator. Statistical data from a large number of simulations, like average and standard deviation, can then be used in the final aggregation.

In figure 2.2 a simulation of three maize mills are shown. The sum of the peak power for three machines are 37 kW, while the simulation gives at hand in this particular case a maximum power of 25 kW only can be predicted, describing that the chance of three milling machines at the same time is most unlikely, but there is certain probability for two machines to run simultaneously.

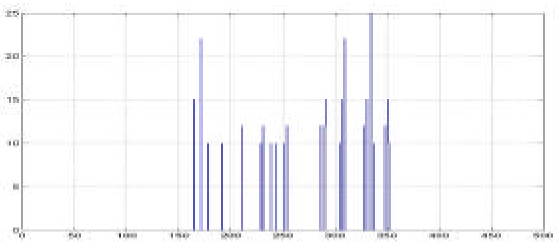

Figure 3.2 *Simulation of three maize mills (10, 12 and 15 kW), showing the aggregated power demand over 24 h calculated at 3 min intervals.*

3.3 Aggregation of load

Aggregation of deterministic and stochastic loads is proposed to be done independently. This means that deterministic loads are summed together (likely) linearly. Stochastic loads, as described by their peak power (and possibly energy content) are summarized geometrical, assuming a clear "un-correlated" behaviour. This implies e.g. that the total power from let say n equal sized loads of P_z kW should be $vn*P_z$, instead of $n*P_z$. For a small group of such loads this difference is significant.

4 Analysis and discussion

A minor modification to the commonly used model for load estimation is suggested, based on in principle the same input data, but slightly differing when it comes to summation over all customer appliances. Two different approaches are suggested, once the data is organized systematically:

1. *Random simulations* can distribute power demand on 24 h basis, down to a given resolution (e.g. 3 min). A number of simulations, e.g. a full year, can be statistically simulated/analyzed and average numbers (and possibly standard deviations) used in assessing peak and average load.

2. Straight forward *geometrical summation* of stochastic loads added to deterministic loads, distributed over 24 h, can give more appropriate indications on the total load, as used e.g. by TANESCO and others.

   The method can be applied even with a small pocket calculator. The separation of ordinary stochastic loads and "critic loads", enable simple analysis of type "what if", that can easily be made in assessing project risks etc.

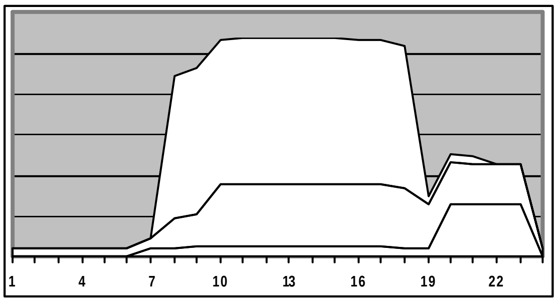

Figure 4.1 *Output from the proposed algorithm*

The output of a simple linear addition of loads from the proposed algorithm is shown in figure 4.1 above, with the deterministic loads at the bottom followed by stochastic loads and finally critic-stochastic loads.

5 Conclusion

The complexity of analyzing small rural load samples has shown that (a) basic information about loads (size and usage patterns) to a large extent is not very well documented and (b) that used load estimation methods often highly overestimate loads. Many existing models for load estimation are using "rules-of-thumb" and based on "ad-hoc" data. When aggregating multiple loads existing estimation models typically use linear addition, (possibly using coincidence factors) to estimate peak power and energy demand.

The proposed algorithm here in principle uses the same input information, but classifies loads in deterministic and stochastic parts. Linear additions are applied to the deterministic loads only where the time distribution is known, and non-linear addition (e.g geometric addition) applied to stochastic and "uncorrelated" loads. By the distribution of loads over 24 h a load matrix will give power profile data, easy to use for designer and planners to properly dimensioning the networks and giving more appropriate data on consumption (energy).

The work has shown a great demand to further systematize load data, find relevant usage patterns, fine tune aggregation modelling and validate the model accuracy.

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References

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