Using system dynamics for long term bottom-up electric load modeling in rural electrification

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Abstract: One billion people lack access to electricity, most of whom live in rural areas in developing countries. A solution to improve their situation is small independent grids, so called minigrids. One of the major challenges for minigrids is to become economically reliable. As electricity usage is a major source of income for a utility, it is important to consider how its fluctuations impacts a utility. This work presents an integration of a previously developed system dynamics model with a comparably detailed bottom-up load model developed in MATLAB. The simulations show that while using a more detailed load model results in an increase in generation capacity expansion frequency and that the investments are made in smaller sizes. Due to the different approach to integrating electricity usage growth, the bottom-up load model shows a faster increase in electricity usage than the system dynamics load model. With a modeled difference on net income, power utilization rate and electricity usage the results indicate that it is important to consider improved load model detail when modeling income and expenditures of an electric utility.

Keywords: bottom-up load modeling, system dynamics, mingrids, rural electrification

Introduction

As of today one billion people lack access to electricity around the world. Roughly half of these people live in sub-Saharan Africa, and a large majority of them live in rural inaccessible areas (IEA, 2013). Improving electricity access for these people is considered an important step towards combating poverty and improve their social and economical conditions. As a service, access to electricity is considered to be a necessary but not sufficient condition for economic and social development (Barnes, 2007; Bhattacharyya, 2013; Goldemberg, Johansson, Reddy, & Williams, 1985). In many cases, using traditional methods such as grid-extension is not enough and if rural communities are to gain the full benefits of electricity access within the foreseeable future, reliable and well managed off-grid solutions are needed. (Ahlborg & Hammar, 2014; Díaz, Arias, Peña, & Sandoval, 2010; IEA, 2013; Tenenbaum, Greacen, Siyambalapitya, & Knuckles, 2014; Urpelainen, 2014)

The size of off-grid solutions varies from tens of W for small Solar Home Systems (SHS) to large minigrids with generation capacity of several MW. The low costs of SHS makes them affordable for single households but their capacity is limited to supply a few low consuming appliances such as: lights and radios. Thereby limiting the benefits that can be obtained from SHS (Azimoh, Klintenberg, Wallin, Karlsson, & Mbohwa, 2016). Minigrids can on the other hand supply enough power and energy to be used for productive activities such as milling, workshops, irrigation pumps, welding and shops/bars. But needs a managing organization and the funneling of resources. Minigrids have been used in rural electrification with various levels of success, with one of the major challenges being their poor economic performance, leading to an inability to reach cost-recovery (Barnes & Foley, 2004; Kirubi, Jacobson, Kammen, & Mills, 2009; Levin & Thomas, 2014; Schnitzer et al., 2014). Their ability to reach cost-recovery has been related to the systems utilization factor (Kirubi et al., 2009; Sarangi et al., 2014). A systems utilization factor is the fraction of actual to maximum electricity generation. In order to improve the utilization factor, generation should be matched with current demand and be appropriately adapted to future demands.

Electric load modeling is a common tool in order to analyze current and future electricity demand. It can be divided into two types: top-down and bottom-up modeling. Top-down load modeling is based on large aggregated data sets and use mathematical methods to analyze and predict demand changes for large groups. Bottom-up load modeling, on the other hand, is based on modeling of the single loads, such as lights and TVs, which are then aggregated to obtain a total user and system load.

One advantage of top-down methods is that they require less consumer data than bottom-up methods. Bucher and Andersson (2012) developed a top-down approach to load profile generation for household load profiles. By using a top-down approach their method could be applied in cases where little or no consumer information is available. However, in general, top-down approaches used for residential loads are less frequent than bottom up methods. Alternatively, they are more often used to aggregated load analyses since their accuracy decrease further down in the system, partly due to lack of integration with human behavior and specific appliance usage.

Bottom-up methods have the benefit that they either directly or indirectly incorporate human behavior (Stokes, 2005). This can be done by defining activities, and then generating load profiles from these activities (Widén et al., 2009). In the case of Widén et al, they addressed e.g. vacuum cleaning but in developing countries it could include activities such as milling, welding or studying. The challenge with bottom-up load modeling methods is that they are relying on large amounts of information about each specific load; data which is often protected by integrity issues or by privacy laws.

Regardless of the choice of method, if the model simulates current electricity consumption they do not likely need to take into account changing socio-economic conditions like electricity price, access to new appliances, income or population. However, if the purpose is to model future consumption with a sufficiently long time scale, local conditions change which needs to be incorporated into the modeling process. Recently, artificial neural networks (Carpinteiro, Leme, de Souza, Pinheiro, & Moreira, 2007), particle-swarm-optimization (Niu, Li, Li, & Liu, 2009) and other artificial intelligence methods have been employed to predict the long term impact of changing conditions on load changes in the western world.

In rural communities in developing countries, where electricity has recently been introduced, it is likely to believe that the time scales for local conditions to change are shorter. Introduction of new electrical appliances can have a substantial impact on electricity provision and livelihoods. E.g. low energy lightbulbs that can reduce electricity consumption and introduction of fridges and freezers, which both have a large impact on electricity consumption patterns and on life style (Madubansi & Shackleton, 2006). Therefore, it is important to consider changing local conditions in electricity load modeling in rural electrification.

System dynamics has been explained as a tool to map system structures to system behavior (Davidsen, 1992). As such it has been used to describe problems related to aggregated socio-economic indicators, such as income, energy usage and environmental impact (Hjorth & Bagheri, 2006; Marzouk & Azab, 2014; Qudrat-Ullah & Davidsen, 2001). In the case of energy modeling in general and electricity modelling in particular, there have been several applications of system dynamics, see Teufel et al. (2013) for a review. However, modeling the elements of aggregated variables falls outside the scope of system dynamics. In the case of electricity usage, system dynamics can be an efficient tool to analyze growth in aggregated electricity consumption but is not suited to model daily load profiles.

A system dynamics model of a utility operating a rural minigrid in a developed country (Tanzania) was presented in (Hartvigsson, 2016). The model focus on the income and expenses of a utility, which is directly linked to electricity usage and generation capacity. However, the model assumes a fixed, linear relationship between electricity consumption and peak load. In reality, the fast daily variations of different user groups are much more complex. Inclusion of these fast variations is likely to result in higher peak loads and, thereby, a higher peak power demand for a given electricity usage. To the knowledge of the authors, no link between a system dynamics electric utility load model and a load model has previously been presented in the literature. Despite the self-evident difference between the two load modeling approaches, the impact and its extent is not known. Therefore, the purpose of this paper is to investigate to which extent improved load modeling impacts a system dynamics utility model. Specifically, does improved load modeling detail impacts a modeled utility's economic performance? Economic performance is defined as the utility's weekly net income during the simulated time period, e.g. differences between income and expenses.

The paper is divided into five sections. First the method of integrating the load model with the system dynamics model is presented. Second, the load model is explained in detail together with input data and assumptions. Based on the two model approaches, a number of runs are shown both with and without an external load model in the Result section. The results and their possible impacts are discussed before conclusions and future work are presented.

Method

This work is based on the system dynamics model presented in (Hartvigsson, 2016). The model employs an aggregated and simplified approach to load modeling (from here on referred to as the Vensim load model), where peak demand is scaled from electricity usage according to $\text{peak demand} = \frac{\text{electricity usage}}{d}$, where d is the number of hours of electricity consumption per week. In order to investigate the impact of increased load modeling detail has on the modelled utility's economy, a stand-alone load model was developed in MATLAB (from here on referred to as the MATLAB load model). The results on the modelled utility's economy and overall electricity usage are then compared between the simplified system dynamics load model and the MATLAB stand-alone load model.

The system dynamics model was developed in Vensim, making it possible to utilize the VenDLL library for handling external calls. The VenDLL library allows external calls to change selected variables during a Vensim gaming simulation. This allows VenDLL to retrieve data from the Vensim simulation, send the data to the load model in MATLAB, run the load model and retrieve its output and then write the changes to Vensim. The communication between Vensim and MATLAB is conducted at each time step, allowing for real time integration of the MATLAB load model into the system dynamics model. Figure 1 shows a conceptual diagram of the modeling process.

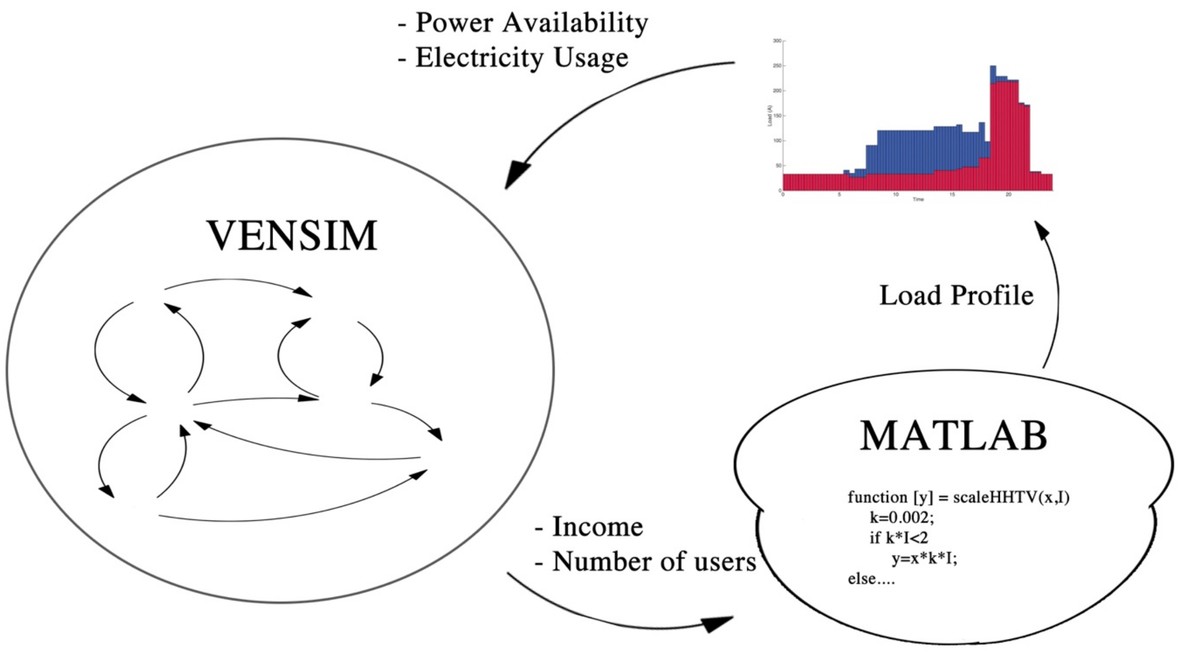

Figure 1 A conceptual diagram of the integration of Vensim with the load model in MATLAB.

The system dynamics model consists of five sectors: user diffusion, utility economics, local market, population and electricity generation. By including the different sectors, the model can give a simplified representation of local socio-economic conditions that directly and indirectly affect electricity usage. It is assumed that the main driver for increase in electricity consumption is income. Income is sent from the system dynamics model in Vensim to the MATLAB load model, which use it to generate individual user load profiles (see the below load model description). The user's load profiles are then scaled with the number of users to obtain the total system load profile.

Both load modeling approaches assumes that if there is an initial generation capacity installed and that the this can continuously produce at its rated power. Depending on the energy source this might not always hold true. Specifically, renewable energy sources are often characterized by having a relative large intermittency. However, modeling individual energy sources characteristics is outside the scope of this work.

Load Model

The implemented load model is a linear bottom-up appliance diffusion model using income and power utilization rate as variables. As a bottom-up load model it models each appliance separately and then aggregates them to generate the system's total load profile. In order to determine the load growth for each appliance, they are assigned two variables: a diffusion rate and a saturation level. The diffusion rate determines how sensitive appliance load growth is to variations in income and the saturation limit marks the maximum occurrence of each appliance. Equation 1 describe the load profile for appliance *i*.

$$\Gamma_i = I \cdot \delta \cdot StdLP_i \cdot N(\mu, \varphi) \qquad (1)$$

Where I is average income, δ is diffusion rate, $StdLP_i$ is the standard load profile for appliance *i* and $N(\mu, \varphi)$ is a normal distribution with mean μ and standard deviation φ. By selecting mean and standard deviation to be 1 and 0.1, the model allows for some uncertainty of each appliance power output at a specific time interval. This reflects part of the uncertainty in when a specific appliance is turned on. In order to obtain the systems total load, the appliance load profiles are aggregated first per user and then for all users. Equation 2 then describes a generic expression for the total load profile.

$$\sum_{k=1}^{m} \sum_{i=1}^{n} \mathrm{U}_k \cdot \Gamma_i \cdot f(\mathrm{Power\_Availbility}) \qquad (2)$$

Where m is the number of user groups, n the number of appliances in each user group and U_k the number of users in user group k. Due to differences in consumption patterns, sensitivity to power outages and power demand, users where separated into two groups: households and Small and Medium Enterprises (SMEs). Users are also assumed to respond negatively to disruptions in the electricity provision, which is expressed by the function f with power utilization rate as only variable. Power utilization rate is defined as the ratio between peak power and maximum generation capacity. If this ratio becomes larger than one, implying that temporary blackouts occur, users are assumed to respond by reducing their electricity consumption. The function f is expressed as a cotangents function, assuming a slow initial reaction that increase as power utilization rate deteriorates.

Load model data and assumptions

The standard load profile for each appliance was identified via a case study in a minigrid in Tanzania (Hartvigsson, Ehnberg, Ahlgren, & Molander, 2015) and rely on both interviews and measurements. The interviews identified four appliances in households: lights, stereo, TVs and DVDs. Some other appliances such as computers and iron where also identified but where concluded to have no impact on average daily load profiles. Figure 2 shows the standard load profiles for each of the appliances using a 30 min time resolution.

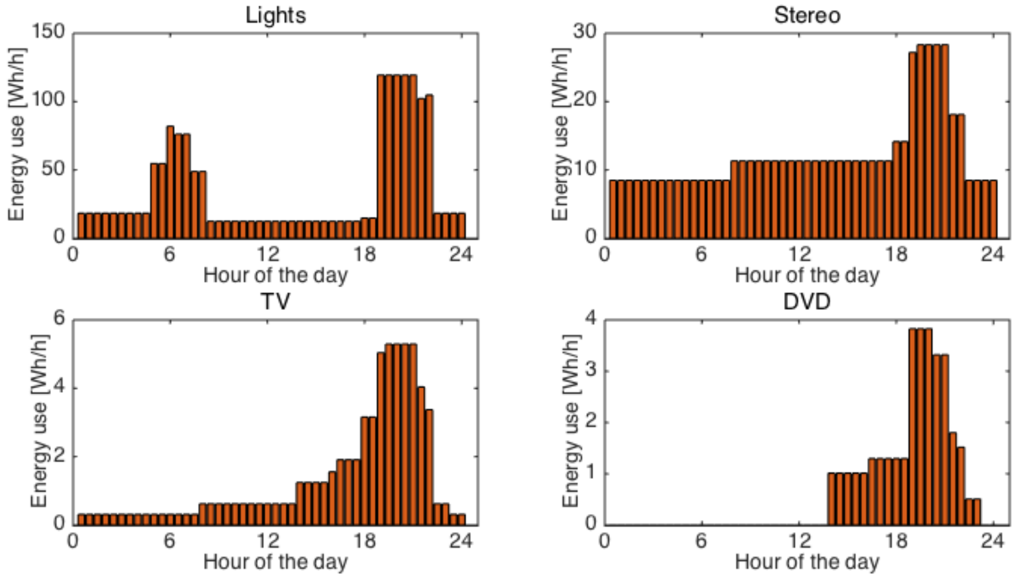

Figure 2 showing standard load profiles for each of the household appliances.

For SMEs a wider range of appliances where identified. Due to their similarity in terms of average electricity consumption some of them where grouped together. This includes the groups “Machines” and “Others” seen below in Figure 3. Machines is a combined load group of high power electric equipment such as electric machines, power tools and electric welding equipment. The group “Others” mainly include low load appliances (such as hair trimmers) or appliances that are very rare (computers and printers). In Figure 3 shows the standard SME load profiles for each appliance.

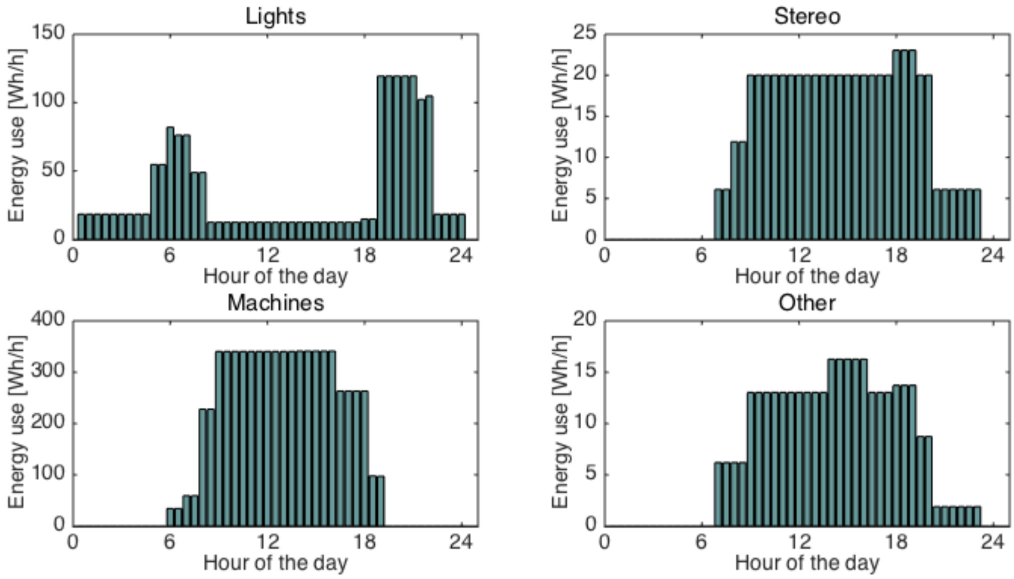

Figure 3 shows standard load profile for each of the SMEs appliances.

As shown in Equation 1, the load profile expression is a linear function of average income. Assuming that no income results in no appliance ownership one data point is required for determine diffusion rate. The diffusion rate for each appliance could therefore be determined using data on income of 29 households and 19 SMEs from a minigrid in rural Tanzania.

The saturation level, which is defined as the maximum occurrence of a specific appliance, e.g. a saturation limit of 14 implies 14 is the maximum amount of appliances per user regardless of income. In some cases data on saturation levels where found. In cases where data was lacking, values were estimated based on observations on appliance occurence and income levels. Diffusion rates and saturation levels for all appliances can be seen in table 1.

Table 1 Showing diffusion rates and saturation limits for appliances for each appliance.

Appliances	Diffusion rate [appliances/USD]	Saturation Limit [# appliances]
Lights (household)	0.39	14[1]
Stereo (households)	0.02	2
TV (households)	0.004	2[2]
DVD (households)	0.03	1
Lights (SME)	0.03	4
Stereo (SME)	0.013	1
Electric Machines (SME)	0.002	0.5
Other (SME)	0.008	1

[1] Data taken on saturation limits for lights in Argentina and Sri Lanka (McNeil, 2008).
[2] Estimated using data from (McNeil, 2008).

Results

The results of running the Vensim and MATLAB load models are presented in Figure 4-7 in the following order. Figure 4 shows the MATLAB and Vensim generated load profiles at initial and final stages. Figure 5 presents the utility's balance sheet and Figure 6 the power utilization rate. Finally, total electricity usage is shown in Figure 7.

Figure 4 shows initial and final load profiles. The dark and light orange load profiles are generated using the MATLAB load model as described in this paper. The dark and light blue lines are generated from Vensim's peak load model, as described in the Method section. Since the load implementation in Vensim is a constant scale between electricity usage and peak load, the Vensim generated peak loads are constant. The solid dark blue line represents the initial Vensim load and the dotted light blue line represents the final Vensim load. The orange load profile was generated by the MATLAB load model. The dark orange graph is the initial load profile and the light orange graph is the final load profile. As seen there is a distinct growth in peak power and electricity usage for the two models, but with a considerable higher peak power shown by the MATLAB load model.

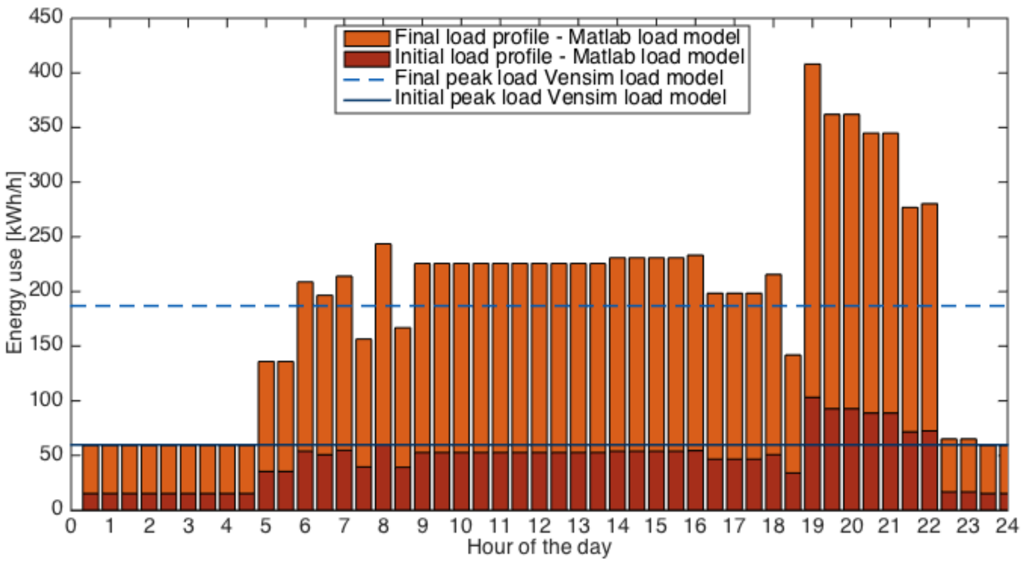

Figure 4 The graph shows initial and final load profiles using the external load model developed in MATLAB and the internal Vensim load model.

Figure 5 shows the utility's net income plotted as a function of time. The blue graph, which represents the Vensim load model shows fewer but larger dips. The dips are explained by sudden large expenses, and is in this case related to the acquisition of new generation capacity. As investments in new capacity depend on power utilization rate, the expenses follow power utilization rate with a delay. As seen in the case with the MATLAB load model, there are more but smaller dips, indicating that expansion is taken place more often but and in smaller sizes.

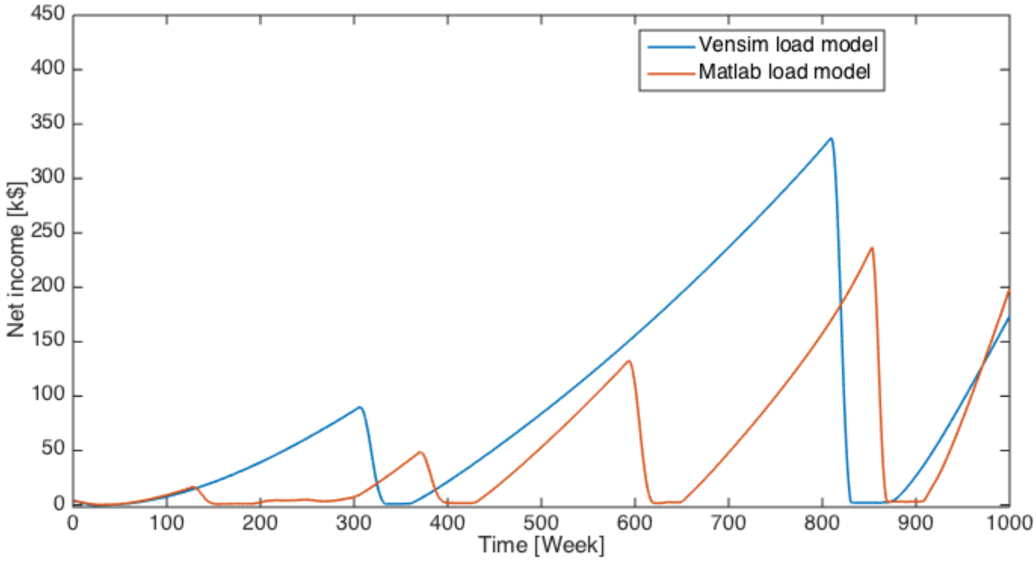

Figure 5 The graph shows the utility's financial balance using the external load model developed in MATLAB (blue graph) and the internal Vensim load model (orange).

Figure 6 shows the power utilization rate plotted over time for the Vensim load model (blue graph) and the MATLAB load model (orange graph). The figure clearly shows a higher overall power utilization rate when using the MATLAB load model. The MATLAB load model is also seen to be showing less fluctuations than the Vensim load model.

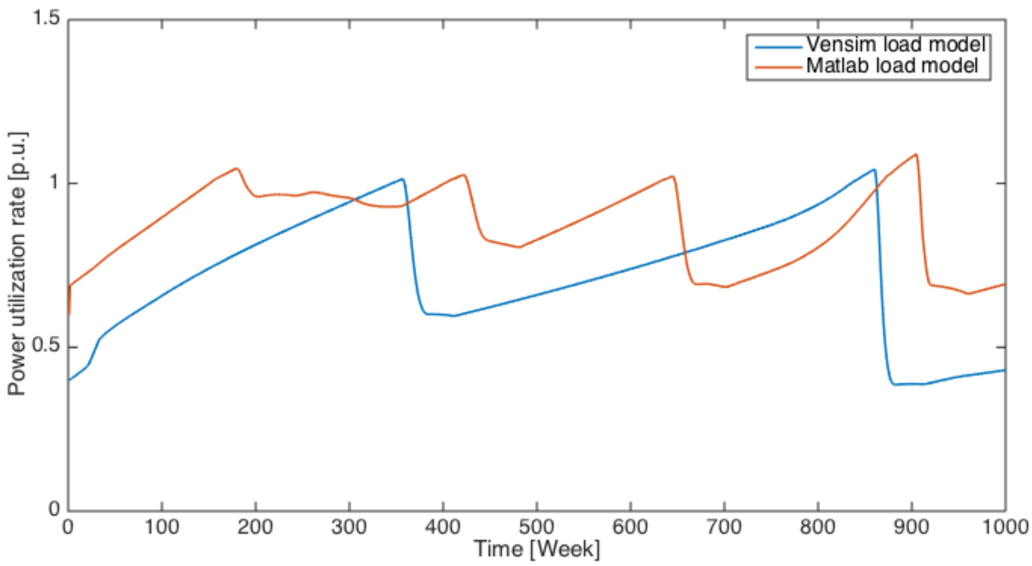

Figure 6 The graph shows power utilization rate, defined as fraction between peak power demand and installed generation capacity, for the external load model developed in MATLAB (orange graph) and the internal Vensim load model (blue graph).

Figure 7 shows total electricity usage for the two models. The blue graph shows total electricity usage using the Vensim load model and the orange graph using the MATLAB load model. The total electricity usage is very similar initially and it is not until after about 300 weeks that they start to diverge with a final difference of about 25%. Even though number of users are not presented in detail in the paper, the number of users are the same for both cases, indicating that it is electricity usage per person that grows faster when using the MATLAB load model.

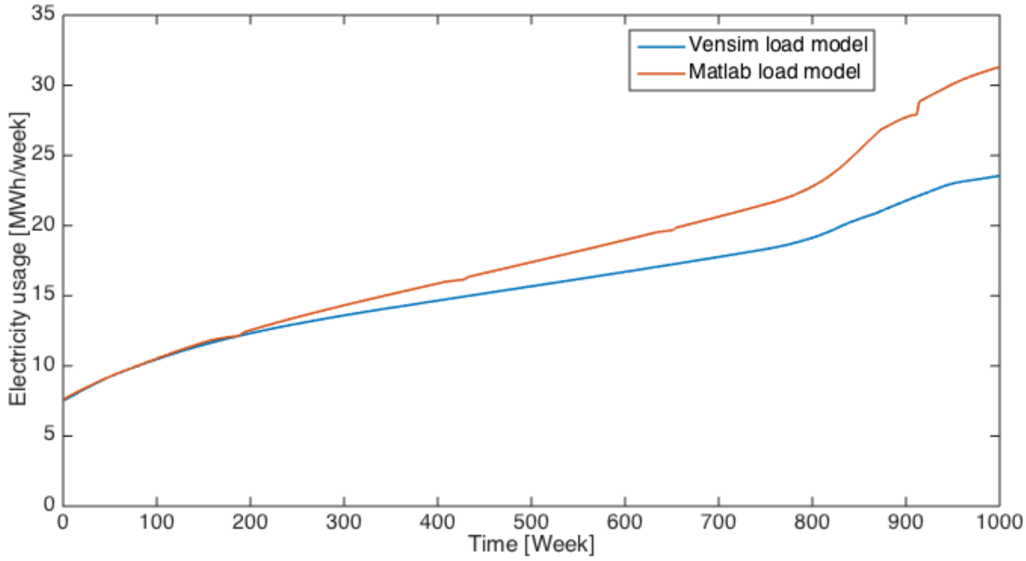

Figure 7 The graph shows total electricity usage in the minigrid for the external load model developed in MATLAB (orange graph) and the internal Vensim load model (blue graph).

Discussion

As shown by the figures, the two modeling approaches generates different results on the modeled utility's net income, power utilization rate and electricity usage. As can be seen in Figure 4 and 7 the MATLAB generated load profiles results in larger peak load for a specific electricity usage. With the increase in peak load the utility has to match with increasing its generation capacity in order to avoid power utilization rate deterioration. The external MATLAB load model therefore requires a larger installed capacity to supply the same electricity consumption, which could have negative impacts on net income. But since total electricity usage is higher in the MATLAB load model case the utility also receives more income.

As can be seen in Figure 7, the MATLAB load model results in higher total electricity usage than the Vensim load model. This might seem unintuitive since the MATLAB load model requires a higher peak load compared to electricity usage, which therefore requires a larger generation capacity (increasing expenses that the utility could have otherwise used for connecting users thereby obtaining a larger total electricity usage) for a given electricity consumption. However, use of the bottom-up appliance diffusion approach increases electricity usage faster (as a function of income) than the Vensim approach. In Vensim increase in electricity usage is proportional to increase in income, e.g. if income increase with 10% electricity usage increase with 10%. One issue with the Vensim approach is that it does not take into account acquisition of new appliances, thereby excluding a feedback loop. The result of the two approaches is a difference in electricity usage sensitivity to income, which as income grows becomes apparent and can be seen in Figure 7. The increase in electricity usage also increase income for the utility allowing it to make the necessary investments in new generation.

When comparing the two models it is important to note that the MATLAB load model is also a simplified load model and excludes certain processes that are common in more advanced load models. One such processes is coincidence. Coincidence, or coincidence factor, is an indicator of the probability that loads will be turned on simultaneously. With a coincidence factor of 0.5, a 50 kW capacity (transmission and generation) is enough to supply an installed load of 100 kW. As described in the method sections, the standard load profiles used in the modeling procedure are based on interviews and measurements. Since the measurements where done at household level the model takes coincidence between appliance loads into account. However, as the total load profile is aggregated from the individual users, the model lacks an integration of coincidence between users. If a full coincidence would be integrated it could allow for more users given the same installed capacity.

Another simplification in the integration between the MATLAB load model and the system dynamics model is through the definition and implementation of power utilization rate. Due to the definition of power utilization rate, it only reflects one point in time. Even though this implementation includes issues with potential power outages it assumes all users are equally affected. This can be especially troublesome if the peak load that deteriorate power utilization rate takes place during the evening, when the load is almost exclusively based on household's electricity consumption. With a decreased power utilization rate, it will impact the electricity usage of both households and SMEs, even though SMEs consumption is mostly during the day and are therefore not affected by the issues to the same extent. These issues could potentially be solved by implementing different power utilization rate indicators for each user group, e.g. one for households and one for SMEs.

Conclusions and future work

By incorporating a comparably detailed load model into an existing system dynamics model, this work has compared the economic impact on a minigrid utility between two different load modeling methods. The results show that the more detailed load model requires the utility to invest in generation capacity at more frequent intervals in order to keep power utilization rate from deteriorating. The results also show that investments in new generation capacity are more frequent, but that each investment is smaller, when the MATLAB load model is used. The bottom-up approach to modeling load appliances (MATLAB load model) also shows a faster growth in electricity consumption

As presented in this work, the improvement of load modeling detail impacts the modelled minigrid utility's balance sheet and its investments in new capacity. However, when matching generation with load it is also important to consider the specific characteristics of different energy sources, in particular intermittent energy sources. While this has been excluded in this work, future work could include integration of capacity expansion choices including renewable energy source characteristics.

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