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Comparison of load profiles in a mini-grid: Assessment of performance metrics using measured and interview-based data

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ABSTRACT

Mini-grids are seen as an important option for increasing access to electricity in non-electrified rural areas where grid-extension is unfeasible. Appropriately dimensioning and constructing mini-grids requires knowledge of electricity usage. There is currently a lack of measured load profiles from mini-grids and the most common method for estimating electricity usage is through appliance data collected via interviews. Thus, this paper compares and investigates the differences between measured daily load profiles and daily load profiles created from appliance data collected through interviews and how the two methods impact the dimensioning and operation of a mini-grid. This is done by comparing load profiles for an entire mini-grid, a household and SME customers with large loads. The paper reports differing results from the two methodologies. Generally, the results show that the interview-based load profiles fail to provide an accurate overall estimate. The calculated performance metrics for the two methods also shows large differences. The interview-based load profiles mainly fail to provide accurate estimates of energy and the energy related (capacity factor and load factor) performance metrics. Accordingly, the implications for mini-grid operators and developers could be significant. The interview-based load profiles indicate the mini-grid system to be considerably less technically and economically desirable than measurements show. Suggestions for how the interview process can be improved are presented.

Introduction

Over one billion people lack access to electricity in the world as of today. Most of these people live in remote rural areas in sub-Saharan Africa and developing Asia (IEA, 2015). Improving access to modern energy sources is considered an important goal in combating extreme poverty. It is the 7th of the Sustainable Development Goals (United Nations, 2015) and the primary objective of the Sustainable Energy for All Initiative (SE4All, 2017). Growth in energy consumption has been identified as correlating with economic growth, for developed as well as developing countries (Cook, 2011; Ozturk, 2010; Wolde-Rufael, 2006). Apart from benefits associated with economic growth, access to electricity has also been identified as having positive impacts on education and health (Independent Evaluation Group, 2008; Kanagawa & Nakata, 2008).

Productive use of electricity (e.g. electricity used for income generating activities) is considered an important way of successfully linking electrification and development (Cook, 2011; Mulder & Tembe, 2008). The creation and modernisation of such activities makes access to reliable and affordable electricity an important precondition of long-term economic growth (Shyu, 2014). Several activities found in rural villages have the potential to be made more efficient by introducing electricity, such as milling, carpentry and increased opening hours for shops. Access to electricity can also lead to the creation of new businesses such as welding, internet cafés, bars selling cold drinks, electrical equipment and battery charging stations.

Historically, improved access to electricity in developing countries has been mostly through grid extension, with recent increased interest in small off-grid systems such as solar home systems (SHSs) and mini-grids. Grid extension has led to a focus on communities close to the grid or larger urban areas, excluding a large section of the population living in inaccessible rural areas (Ahlborg & Hammar, 2014; Díaz, Arias, Peña, & Sandoval, 2010; IEA, 2015; Tenenbaum, Greacen, Siyambalapitya, & Knuckles, 2014; Urpelainen, 2014). Off-grid systems provide an alternative in rural areas and are considered necessary in order to meet current electricity access goals (Tenenbaum et al., 2014). SHSs are relatively cheap but do not have the capacity to sustain many productive uses, which limit their impact on economic development (Azimoh, Klintenberg, Wallin, Karlsson, & Mbohwa, 2016). Mini-grids are large enough to support productive use activities. They are defined as small, independent electricity generation and distribution systems, supplying from a hundred to a few thousand customers.

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One of the major challenges relating to the dissemination of mini-grids is their poor economic performance, leading to an inability to cover operating and expansion costs (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 mini-grid's capacity factor (Kirubi et al., 2009; Sarangi et al., 2014). A mini-grid's capacity factor is the ratio between maximum possible electricity generation and actual generation of electricity. To utilize a mini-grid efficiently, the capacity factor should be as high as possible. To maximize it, generation needs to be matched to current electricity consumption and be appropriately adapted to handle future changes. Thus, both short-term variations (such as daily load profiles) as well as long-term developments need to be sufficiently known.

Even though long-term developments in electricity and overall energy consumption in recently electrified areas very from case to case, the trend seems to indicate an overall increase in consumption over time. Pereira, Freitas, and da Silva (2010) analysed the long-term behaviour of 23,000 rural properties in Brazil and found that in four years there was a large increase in overall energy consumption amongst electrified properties. Díaz et al. (2010) found similar tendencies when they investigated the total system electricity demand of 16 sites in the Jujuy province, Argentina over seven years. These studies investigated long-term developments of total demand, but as Palma-Behnke et al. (2013) and Mandelli, Brivio, Colombo, and Merlo (2016) found, the daily demand variations in mini-grids are also important, especially for mini-grids relying on a large share of renewable energy sources.

Access to reliable, high-resolution data on electricity consumption in developing countries is sparse (Cross & Gaunt, 2003; Nfah, Ngundam, Vandenbergh, & Schmid, 2008). Due to the data scarcity, several studies have relied on alternative data sources or methods. Sen and Bhattacharyya (2014) found most studies did not consider measured load profiles when conducting technology assessments of mini-grids based on renewable energy sources. Instead, they used synthesized hourly load profiles based on collected appliance data. Boait, Advani, and Gammon (2015) analysed daily demand profiles for off-grid electrification in developing countries, using a similar method. A result of using data on appliance power rating and usage data is that the demand profiles have an hourly resolution. This means they may omit the impact of rapid changes, such as peak demand arising from the switching appliances on and off. Moreover, appliance data collected via interviews and/or questionnaires suffers from uncertainty in terms of usage patterns and power ratings. Blodgett, Dauenhauer, Louie, and Kickham (2017) investigated the accuracy of electricity assessments from appliance-specific data for small micro-grids (1.5–5.6 kW) and found large discrepancies when compared to measured electricity consumption. In an study of load profiles constructed from appliance data obtained from interviews, Hartvigsson, Ehnberg, Ahlgren, and Molander (2015) found discrepancies when compared with actual measurements.

Having access to accurate estimates of load profiles is important if high capacity factors are to be achieved and for successful implementation of mini-grid projects (Sarangi et al., 2014). If generation capacity is over-dimensioned, mini-grids risk suffering from poor economic performance. Similarly, if generation capacity is under-dimensioned, then technical functionality can be reduced, with negative effects for the operator. A lack of accurate data on load profiles has been identified in the literature. Cross & Gaunt, 2003 developed a residential load model for rural South Africa and identified a lack of data as the greatest problem in creating accurate models. Similarly, Wijaya & Tezuka, 2013 found a lack of electricity usage data to be the largest barrier to accurately studying household electricity consumption and thereby formulating efficient policies. A similar conclusion was drawn in a report by the World Bank. It concluded that access to high quality load data is necessary if appropriate technology investments is to be made in mini-grids (Terrado, Cabraal, & Mukherjee, 2008).

A common method of generating load profiles when measurements are unavailable is to use appliance-specific data such as power rating and usage (Blodgett et al., 2017; Boait et al., 2015; Mandelli, Merlo, & Colombo, 2016; Sen & Bhattacharyya, 2014). When obtained from interviews, this can provide a simple and resource-efficient method of estimating load profiles in already existing mini-grids. However, using load profiles from interviews affects the accuracy of the load profiles (Hartvigsson et al., 2015). The extent of the differences between load profiles constructed from appliance data and those from measurements is currently unknown. Consequently, the implications on dimensioning and operation of mini-grids arising from these differences is also unknown (Blum, Sryantoro Wakeling, & Schmidt, 2013; Cross & Gaunt, 2003; Hartvigsson et al., 2015). Previous work has been limited, either to describing the differences between the two methods (Hartvigsson et al., 2015) or to comparisons of energy consumption (Blodgett et al., 2017). It has not assessed any impact on mini-grid dimensioning and operations, or ways in which interview-based load profiles could be improved to give more accurate load assessments. Thus, the purpose of this paper is to assess the implications of using interview-based load profiles on mini-grid dimensioning and operation. Specifically, the paper aims to answer the following question.

- Do the differences between the load profiles based on appliance data collected through interviews and those based on measurements have implications for the dimensioning and operation of mini-grids?

The investigation involved comparing and analysing load profiles from appliance data collected from interviews with measurements using the same data-set as in (Hartvigsson et al., 2015). The measured data set is available for download and can be found under Complementary Material.

The paper is divided into five sections. First, the method is presented, including the two different data collection methods and load profile generation. This is followed by a description of the case to which our method is applied. Next, there is a presentation of load profiles and operator performance metrics based on high-resolution measured data and interview data. The results are followed by a Discussion section divided into three subsections focusing on: causes of differences, impacts on dimensioning and operation and improvements of the interview-based data. Conclusions are then drawn.

Method

To identify how load profiles from interviews can be improved and to investigate the impacts of interview-based load profiles compared to those determined from measurements, a set of load profiles was generated and measured in a rural Tanzanian village. The load profiles were generated and measured at three levels; 1) households, representing the major customers; 2) small and medium sized enterprises (SMEs) with large loads representing income-generating productive use; and 3) for the entire mini-grid. Although individual households consume relatively little electricity, they represent the majority of the customers and thus likely the majority of the load. SME customers with large loads are fewer by comparison, but their individual electricity consumption is considerably more, in terms of both energy and power. Hence, their individual impact is greater. Since not all customers (especially SMEs) use all their electric appliances on weekends, load profiles were collected and generated for weekdays and weekends (Sundays). Due to the different load characteristics between households and SMEs, the differences between interview-based load profiles and measured load profiles needs to be analysed separately for households and SMEs. Furthermore, to identify how well interview-based load profiles scale when compared to measurements, the load of the entire system also needs to be investigated.

In addition to its households and SMEs, the village included a local hospital. However, due to the number of appliances in the hospital, it was considered unrealistic to estimate the total hospital load by collecting appliance data through interviews. The hospital is therefore excluded from the comparison.

Interview-based load profiles

Data collection

The interview-based load profiles were constructed from appliance and usage data that was collected through questionnaires with complementary open questions. Interviews were conducted between 9:00 and 15:00. The interviews began with the questionnaire, and its predefined questions on household size, economy and electricity usage. The questionnaire segment on electricity usage had questions with pre-set answers regarding number and type of appliances, usage duration, time of use and on which weekdays the appliance is used; e.g. “Does your household have a TV?” followed by “What time is the TV used?” and “Which days are the TV used?”. The answers to the questionnaire were then used as a starting point for more specific open-ended questions regarding usage patterns. The open-ended questions were used to verify the answers on electricity usage from the questionnaire. If a customer had a TV, they could be asked what they usually watched on TV and this could be compared to their previous answer on time of use and for how long they used it every day. In cases when respondents could not answer at what time appliances were used (e.g. the person being interviewed did not regularly use the appliance), average running times from the other respondents were used. As appliances' power ratings are rarely identical (even for the same type of appliance), their appliances power ratings were verified by inspection when possible. If power ratings could not be verified, as much information as possible was collected on appliance features, such as size of TVs and type and size of stereos. This was used to estimate a power rating based on appliances with similar features. Additional information was collected regarding the large loads used by some SMEs. This information included duration of operation each day and opening hours. A Swahili to English interpreter was used because none of the interviewees spoke sufficiently good English.

Since it was unfeasible to conduct interviews with all the mini-grid customers, 47 customers were chosen who were estimated as representative. The selection of customers for interviews was based on their estimated socio-economic status and on geographical location. Socio-economic status was determined by visually assessing the customer's buildings and property alongside discussions with a local guide. This was done in order to capture the socio-economic diversity of the customers. Socio-economic factors include households size (in terms of occupants), years since electricity was connected, farm size (in ha) and quantity of livestock. Geographical location was taken into account to ensure that customers both on the perimeter and at the centre of the mini-grid were included. It was deemed important to include customers on the perimeter and at the centre as, due to technical limitations, customers on the perimeter are more likely to suffer issues of reduced power quality, such as voltage drops, which could affect their usage.

Generation of interview-based load profiles

Based on the interview data, power rating and running times were extracted for each appliance and used to construct appliance-specific load profiles. An average household load profile was constructed so as to generate a load profile for the total household load. The average household load profile is constructed by considering all appliances which are used at time *i* scaled by the ratio between interviewed household customers (n) and total number of household customers (N). The calculation for the load (E_i) at time *i* is shown in Eq. (1). This approach assumes no coincidence. Furthermore, in order to make a specific comparison with measurements on household level, one household was selected (considered average in terms of the socio-economic attributes).

$$E_i = \frac{N}{n} * \sum_{m}^{n} P_{m,i} \tag{1}$$

There are also household appliances that are used over shorter periods at high power (such as irons). Their contribution to the load at time *i* is calculated by evenly dividing their rated power (*P*) by their usage time (t_{usage}) as is shown in Eq. (2).

$$E_i = \frac{P}{t_{\text{usage}}} \tag{2}$$

The above procedure could not be implemented for the large loads, due their irregular power demand and running times (electric machines for example). A different procedure was used to determine these load profiles. The load's daily energy consumption was calculated based on the rated power of the load and the daily usage time (t_{usage}), given by the respondents as the number of hours the machine was used each day. Because it was difficult for the operators to specify at what times their machines where running, the daily energy consumption was uniformly distributed during their business hours (t_{open}), resulting in a constant power demand. The calculation for the load at time *i*, is shown in Eq. (2), where k is the number of customers with large loads.

$$E_i = \sum_{m}^{k} P_m * \frac{t_{\text{usage}}}{t_{\text{open}}} \tag{3}$$

The procedure used for the households was used to generate the load profile for the smaller SME appliances. To construct an interview-based load profile representing all SMEs, all appliance load profiles for the interviewed SMEs were aggregated into a single load profile. The entire mini-grid system load profile was then obtained by combining the load profiles for households, SMEs and the large loads.

Measured load profiles

The load measurements were carried out using four Amprobe TRMS-16 Pro current clamp-on current meters. These meters are clamped around a conductor and measure the True Root Mean Square (TRMS) current. A clamp-on current meter has the advantage of not needing any rewiring in order to be connected, thereby increasing accessibility and security of measurements. Since each device can only measure at a single-phase at the time and because there was a limited number of devices, measurements where only taken in a single-phase. When converting between three-phase and single-phase loads they are assumed to be balanced, e.g. the three-phase load is equally distributed amongst the phases. Since the clamp-on current meters measures current while interviews collected data on power ratings, current was estimated from appliances power ratings assuming nominal voltage (230 V AC) and a power factor of 0.85 (Kjellström, Katyega, Kadete, Noppen, & Mvungi, 1992; Rahman, Paatero, & Lahdelma, 2013). Measurements of voltage were conducted at a later visit and showed differences in voltage levels at various locations. Each location showed bursts or drops in voltage levels, but were stable overall.

Four devices were used in all, allowing simultaneous measurement at multiple locations. Each device measures and stores minimum, maximum and average TRMS current every minute for up to 88 h. The meters were connected at the hydropower plant (measuring at the low-voltage side of the transformer, which is delta-star connected thus ensuring that the phases are balanced), two mills, the local hospital, one workshop and one household. The hydropower plant was chosen to get an indicator of the entire village's load profile. The mills and workshop were chosen since they represented SMEs with the largest loads in the system. As most customers are typically households, measurements were taken in one average household (see Data collection for details). Measurements at each location were taken for a minimum of 88 h. Measurements at the hydropower plant were taken for 240 h (10 days), in order to capture any differences between weekdays and the weekend. Since measurements were done on multiple days, and construction of an average load profile would remove the rapid variations captured by these measurements, one day that was considered representative was chosen from the sample for each customer type. As the hospital was excluded from the comparison, measurements at the hospital were taken so that they could be subtracted them from the load profile measured at the hydropower plant.

Assessing potential impacts

Electricity usage impacts operators through a wide range of complex socio-economic-technical factors and processes (Ahlborg, 2015; Kirubi et al., 2009). Since the purpose of the study is to evaluate the differences between measured and interview-based load profiles, factors were limited to technical factors which directly impacted the dimensioning and operation of mini-grids. Potential impacts were therefore evaluated based on the following five factors: energy, capacity factor, peak load, load factor and coincidence factor (for the large SME loads) (Saadat, 1999). The capacity factor of an electric power system is defined as the fraction of generated electricity and maximum possible generation of electricity over a time frame (T). To avoid seasonal variations, the time frame is usually one year or longer. Since it was not possible to conduct measurements over a full year or to collect data on yearly variations from the interviews, the time frame considered was one week. Using one week as a time frame, variations within the week are captured while variation between weeks (such as seasonal variations) are not captured. Eq. (4) shows the general expression for calculating the capacity factor of a hydropower based system. T is the time frame, P_L is the load served at time t and P_G is the capacity of the generation unit.

$$Capacity\ Factor = \frac{\int_0^T P_L(t)dt}{P_G \cdot T}\# \tag{4}$$

The peak load in a system is the maximum power demand recorded over a specific time period. It is the minimum power that a system must to be able to supply in order to fulfil demand at all times. The time period used to record the peak load was 10 days and therefore includes variations between weekdays but excludes variations between weeks and seasons. A systems load factor is the fraction between average load and peak load. The load factor indicates whether there are large demand variations within a system. A low load factor equals large variations. Eq. (5) shows the general expression for calculating the load factor. $P_{L,\ Avg}$ is the average load and $P_{L,\ Peak}$ is the maximum measured (or generated) load.

$$Load\ Factor = \frac{P_{L,Avg}}{P_{L,Peak}}\# \tag{5}$$

The coincidence factor is a measure of the likelihood of electric loads being used simultaneously. It is calculated as the fraction between maximum measured (or generated) load ($P_{L,\ Peak}$) and total installed load ($P_{L,\ Tot}$). The coincidence factor is especially important for large loads because, if they are run simultaneously, they have a major impact on the overall demand in a system. This is especially so if their size is comparable to the system's generation capacity. A higher coincidence factor suggests there is a higher probability of loads being used simultaneously. The measured (or generated) maximum load needs to be properly identified if accurate calculations of coincidence factors are to be made. This usually requires long time series data. Since the time and measurement devices were limited, the coincidence factor was calculated based on measurements over three days. Eq. (6) shows the general expression for calculating the coincidence factor.

$$Coincidence\ Factor = \frac{P_{L,Peak}}{P_{L,Tot}}\# \tag{6}$$

The case

The study was conducted in a village located in the southwestern highlands of Tanzania. The village, which has roughly 3000 inhabitants and was chosen because it has had a mini-grid system in place for over a decade and because it supplies relatively few customers. The small number of customers reduces the ratio between the total number of customers and number of interviewed customers, thus reducing sample uncertainty. Furthermore, the familiarity with electricity likely improves customers' ability to estimate their electricity consumption patterns when compared to a community which gained access to electricity more recently. The main activities amogst villagers is agriculture with some villagers also engaged in forestry.

The mini-grid is supplied with electricity from a nearby hydropower plant with an initial installed capacity of 120 kW (equal to a phase current of approximately 173A, assuming a balanced load). The mini-grid was initially constructed in 2001. The turbine is of the propeller type[1] and always fully loaded. During times of low load, excess production is dumped to a heat load at the hydropower plant. The heat load is located before the transformer and thus excluded from the measurements. The mini-grid covers an area of approximately 2500 ha and customers are supplied through an 11 kV transmission system and a 400 V distribution system. One local engineer is responsible for the maintenance and operation and is assisted by a technician and a small administrative workforce that is shared with the local hospital.

Income is generated using a flat-tariff payment scheme. This implies that each customer pays a fixed price every month based on their estimated load. The specific method used by the utility for estimating the load was unclear, but the general rule was that customers with larger loads (such as electric machines, large stereos or battery chargers) paid more. The tariff ranges from TZS 5000 to 35,000 (Tanzania shillings) per month, equal to about 3 to 20 USD using exchange rates from November 2014. The TZS 5000 price was generally aimed at households and the TZS 35000 towards SMEs with large loads, e.g. electric machines, power tools or welding equipment. All households interviewed paid the TZS 5000 TZS tariff while for SME the tariff varied from TZS 5000 to 35,000 depending on their installed load.

At the time of data collection, the mini-grid supplied 264 customers. Of these 264 customers, 19 SMEs and 28 households were interviewed ($n = 47$). From the interviews, appliance type and occurrence of appliances were identified, as well as verified power ratings (when possible). Appliances were categorised as either household or SME. The most commonly identified appliance in households were lights (incandescent lightbulbs and fluorescent tubes) followed by TVs. For the SMEs, the most commonly identified appliances were also lights followed by large loads. Tables 1 and 2 shows a compilation of the interview data. Due to the use of 'soft' metrics to describe appliances such as size of TVs (when rated power could not be verified) and the few number of appliances identified for some types (computer, trimmer and hairdryer), using a confidence measure would not be representative. Thus, no confidence measure is presented.

Data collected on the socio-economic indicators mentioned in the Method section are shown in Table 3. Based on the data collected for all households, the table shows average, standard deviation and range. The table also contains data on the socio-economic indicators for the

[1] Turbines used in hydropower plants are generally divided into three types: propeller, pelton and francis. Propeller turbines have a linear efficiency curve and are suitable when the turbine is operated at full load.

Table 1
Appliances identified in the interviews, their occurrence and verified rated power. The "-" sign indicate no verification of rated power or calculation of confidence measure was possible. For power, the assumed power is therefore noted in brackets. An "*" sign indicates cases when only one interviewee had the appliance and thus no confidence value could be calculated.

Appliance type	Mean number of appliances per customer	Average rated power (W) (that was verified by inspection)	Usage			
			Start time (average)	Standard deviation (hours:min)	Stop time (average)	Standard deviation (hours:min)
Households						
TV	0.81	88	16:00	5:00	22:00	0:45
DVD	0.6	14.3	17:30	2:15	21:30	1:00
Stereo	0.5	100	19:00	8:30	21:30	1:15
Lights	8.6	29.5	18:00	4:45	21:00	4:00
Iron	0.4	1000	7:15	2:30	10:15	1:00
SMEs						
Lights	1	27	14:30	5:30	20:30	1:15
Stereo	0.4	75	9:30	3:45	20:45	1:30
DVD	0.2	- (14.3)	10:45	5:00	21:30	1:45
TV	0.3	60	10:30	4:30	21:15	1:30
Computer	0.16	Intel Pentium 4[a]	8:00	1:30	19:30	0:45
Trimmer	0.21	- (15 W)	8:00	1:30	21:30	2:00
Hairdryer	0.16	65	14:00	*	16:00	*

[a] An Intel Pentium 4 computer is assumed to use 150 W of continuous power. The computers were also fitted with TFT screens (15–19 in.) with an assumed continuous power consumption of 20 W.

measured household. The measured household has a slightly larger than average household size, slightly shorter than average years since connected, slightly smaller than average farm size and more than average number of livestock.

Results and analysis

The interview-based and measured load profiles for the entire system are presented first. Fig. 1 shows the result of the interviews and measurements for the entire mini-grid on a weekday (top) and a Sunday (bottom). Table 4 shows the performance metrics calculated for the entire mini-grid. Fig. 2 shows the results of the interviews and measurements for the household, while Table 5 shows the associated performance metrics. Fig. 3 shows the results of the interviews and measurements for the SMEs with large loads and Table 6 shows the associated performance metrics. The results in the figures are presented with the loads per phase given in amperes (A).

The weekday profiles in Fig. 1 show differences between the two methods can be observed in four distinct instances. Firstly, the interview-based base load (12A) is very small compared to the measured base load (90A). Secondly, the interviews do not identify the morning peak at around 6:00, as observed in the measurements. Thirdly, the interview-based evening peak is smaller compared to the measured evening peak. Lastly, the improved resolution and level of detail from the measurements reveals numerous short, and high peaks of demand during the day (9:00–16:00).

Furthermore, the interview-based load profiles for Sunday (shown in Fig. 1) shows a large underestimation of the night and base loads. The base load for the weekday and Sunday interview-based load profiles are identical. Unlike the weekday load profile, the interview-based load profile for Sunday shows a large morning peak. The morning peak is associated with the use of irons, which are used only once per week, before the Sunday service. Similar but smaller morning peaks are also seen in the measurements. The fact that there are multiple peaks can be explained by different churches having their services at different times. Both the interview-based load profile and measurements shows a lower daily consumption than for the weekdays. The reduced daily consumption is explained by many of the SMEs not being open on Sunday (all of the SMEs using large loads responded that they were closed on Sundays).

Table 4 shows the performance metrics for the weekday and Sunday load profiles. Because the night load and daily load on Sunday were not correctly identified, the energy related metrics (energy, load factor and capacity factor) are considerably lower for the interview-based load profile. The large difference in energy produces a considerable gap (about 50%) in the calculated capacity and load factor. However, the peak load and coincidence factor shows a smaller difference.

Fig. 2 shows the household load profiles. Differences between the two methods are observed in three distinct instances: night, day and evening. The first and largest discrepancy between the two methods for the household is much lower night load in the interview-based load profile. The interviews estimate the night load to be roughly six times lower than the measurements. Secondly, the measurements show a decrease in load during the day, which the interviews do not identify. The measurements identify the day load to be roughly three times higher than the load found by the interviews. In addition, the interview-based load profile underestimates the evening peak compared to the measurements. Finally, the difference between the evening load and the night load is noticeably larger for the interview-based load profile. The measurements also identify a spike around 18:00. Considering the size and length of the spike, it is unlikely to be caused by usage of any appliance but rather due to an impedance fault. The distribution grid is generally weak, and thus fault currents are small.

Since measurements were only carried out in one household, it was important to ensure that it was representative. Assuming the measured night load for the entire system to be distributed equally amongst all

Table 2
Appliance and usage data for the large SME loads.

Business type	Number of business	Number of appliances identified	Average rated power (W) per appliance	Range of appliance power rating (min-max)	Usage	
					Average time used per day (hours:min)	Average business opening hours (hours:min)
Milling and pressing	6	8	12,700	1100–18,500	3:45	7:45–17:45
Metal workshop (incl. welding)	2	4	2275	220–6000	6:00	10:30–18:00
Wood workshop	1	2	10,350	2200–18,500	8:00	9:00–18:00

Table 3
Socio-economic indicators used to identify households. The table contains: average values, standard deviation and range.

	Household size (# persons)	Years since connection	Farm size (ha)	Quantity of livestock
Average	3.9	3.7	3.5	13.5
Standard deviation	1.4	3	2	8.9
Range (min-max)	1–6	0–13	1–8	2–38
Measured household	4	3	3	20

households and that SMEs do not contribute to the night load, each household's night load would be approximately 1.1 A; is similar to the measured household night load of 1 A. Similarly, assuming the evening peak value of approximately 130 A would be equally divided, each household's evening peak load would be 1.6 A. This can be compared to the measured household's evening peak of approximately 1.66 A(ignoring the burst peak). The measured household should therefore represent the night and evening loads relatively well.

Table 4 shows the performance metrics calculated for the household. These show major differences (a factor of more than three) between calculated energy for the two methods. There is also a major difference (a factor of more than two) in peak load. This is mostly due to the spike in the measurements observed at 18:00. It is also seen that the coincidence factor for the measurements is greater than 1, suggesting that not all appliances were identified during the interviews.

According to the measured load profiles for the SMEs with large loads in Fig. 3 there are large and fast variations associated with the switching the machines on and off of the machines. In terms of daily time of use, the results from the measured load profiles corresponds relatively well to the interview-based load profiles. Differences are especially clear during the morning and with minor differences in the evening. The measurements do not show any electricity usage in the morning even though the interviews identified usage from 18:00 and onwards. In the afternoon, the measurements show electricity usage until 19:00 while the interview-based load profile only show electricity usage until 18:00.

The peak load from measurements reach 63 A only once, while the interview-based load profiles show a peak load of 61 A over 7 h. The measured load of the three customers exceeds 30 A 10% of the usage time, while their total installed three-phase rated load is 65 kW (equivalent to a phase current of approximately 94 A). The relatively large difference between measured and rated load is likely explained by the fact that the large loads are rarely, if ever, used under full load conditions and that they are rarely, if ever, run at the same time (the local operator has a running scheme for when each of the machines is allowed to run). Thee total installed three-phase load for the nine largest loads in the system is 131 kW (equivalent to a phase current of approximately 190 A).

Table 5 shows performance metrics for the SMEs with large loads. These show a very large difference (more than a factor of six) on calculated energy for the two methods. Due to the spiky behaviour shown by the measurements, the load factor is also considerably lower (more than a factor of six) for the measurements. Both methods identify a similar peak load and coincidence factor.

Discussion

This paper has presented load profiles generated from appliance data collected through interviews and compared them with measured load profiles. Using these load profiles, a number of performance metrics (Peak Load, Energy, Load Factor, Capacity Factor and Coincidence Factor) have been calculated. The load profiles and performance

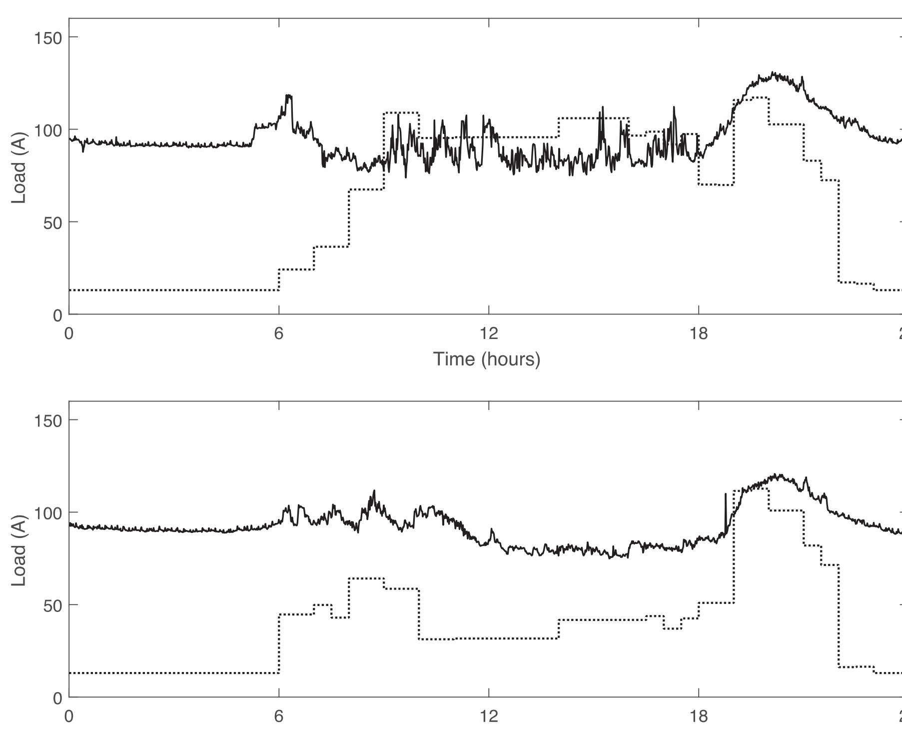

Fig. 1. Load profiles for the entire system for a weekday (top) and Sunday (bottom). The measurements are shown as a black line with one minute's resolution. The black line shows each minute's measured average load. The interview-based load profile is shown as black dotted lines.

Table 4
Load factor and capacity factor calculated from the interview-based load profiles and the measurement-based load profiles for the entire system. The table also shows coincidence factors for the interview-based load profiles and the measurements for the SMEs with large loads.

	Measurements		Interviews	
	Weekday	Sunday	Weekday	Sunday
Load factor	0.72	0.76	0.53	0.35
Peak load (A)	131	121	117	113
Coincidence factor	0.41	0.38	0.37	0.43
Energy (kWh)	1523	1566	1030	658
Capacity factor	0.53		0.34	

metrics show discrepancies between the two methods in a number of areas. The discussion is divided into three areas; area one focuses on the cause of the differences between the methods; area two focuses on the impacts that the results of the two methods have on dimensioning and operation; area three focuses on possible improvements for the interview-based load profiles and performance metrics.

Causes of differences

The largest discrepancy between the two methods is seen in the night load. The interviews estimate the entire system's night load at roughly 37 W per household compared to the measured night load of roughly 280 W per household. According to the appliance data collected from the interviews, the appliance most likely to be responsible for this large discrepancy is high powered light bulbs (80–100 W). Even though high-powered lightbulbs were observed and identified in the interviews, too few were found to fully explain the size of the night load. Furthermore, the operator had regulations in place limiting the usage of high powered lightbulbs. However, interviews revealed that the rules were ambiguous and often not followed. This could explain why few high powered light bulbs were identified. A year after the data was collected, the operator reported that they had initiated a campaign to remove all high powered light bulbs from households. The interview-identified night load of this study (37 W), and the night load identified by Blum et al. (2013) through interviews (16 W) and the measured night load presented by Nfah et al. (2008) (37 W) are all considerably lower than the measured night load (280 W) presented in this study. Problems of correctly identifying the night load were also identified by Mandelli et al. (2016). Since rules regarding the usage of high powered light bulbs were ambiguous this could explain why households were unwilling to reveal their usage, and why they were therefore not fully identified in the interviews.

Another area of difference between the two methods concerns the lack of a morning peak in the interview-based load profiles for the household during weekdays. The village is focused around small-scale agriculture and the farmers get up early in the morning to tend to their land. The measured morning peak likely corresponds with lighting as it corresponds well with the sunrise. Since the interviews were carried out during the day, the person attending the land was rarely available to answer questions. Thus, one explanation to why the morning peak was not identified is that those most often using morning appliances also spend their daytime out on the land. Another possible explanation was through the formulation of the questionnaires. The interviewees may have only indicated answered only when the appliance was mostly used.

Table 5
Calculated performance metrics for the measurements and interview-based load profiles for one household.

	Measurements	Interviews
Energy (kWh)	5.4	1.6
Peak load (A)	2.88 (1.66)	1.27
Load factor	0.34	0.22
Coincidence factor	1.31	1

For the SMEs, the largest difference is the estimating of energy. Energy overestimated due to the constant, high power demand shown in the interview-based load profiles and the short burst of power demand shown by the measurements. The large SME loads consisted mostly of electric machines, power tools or electric welding equipment that was only operated when there was work available and large load variations thus occur naturally. This made running times short and hard to predict. This behaviour also made it difficult to make accurate predications through interviews. However, this it also affects measurements, since if the runs are random, a single day's measurement will not be representative and measurements over multiple days would be needed to acquire a reliable estimate. The accuracy of interview-based load profiles could be improved by dividing running times into short, randomly distributed periods. This would yield a better estimate of energy, but would probably worsen the estimate of peak load.

The peak load of the interview-based load profile and the maximum values of the measured load profile for the SMEs with large loads correlate relatively well. Nonetheless, a difference can be seen in the running times. This difference in running times is clear in the morning, when the interviews indicate that some of the loads begin 3 h before the measurement shows any load. This early morning start was only identified in the interviews for one customer. Furthermore, during the interviews, customers were asked to specify their general usage. Since measurements were conducted over a short time period (three full days), it is likely that the SME customer with a deviating usage did not start early on these specific days.

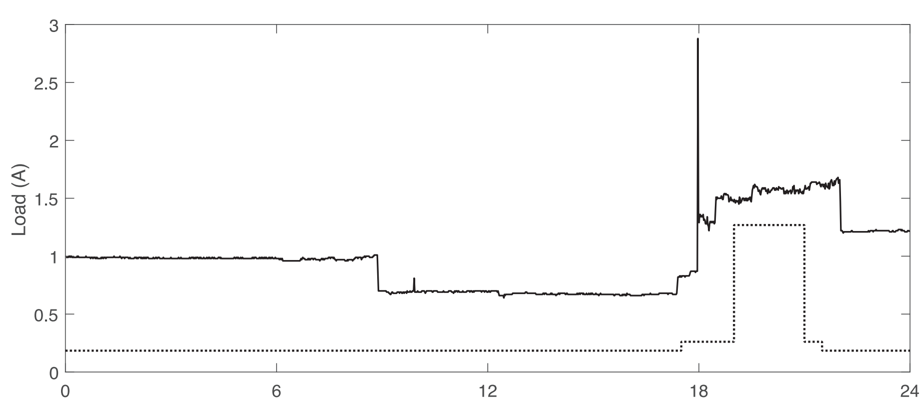

Fig. 2. Load profiles for the household. The measurements are shown as a black line with one minute's resolution. The black line shows each minute's average measured load. The interview-based load profile is shown as a black dotted line.

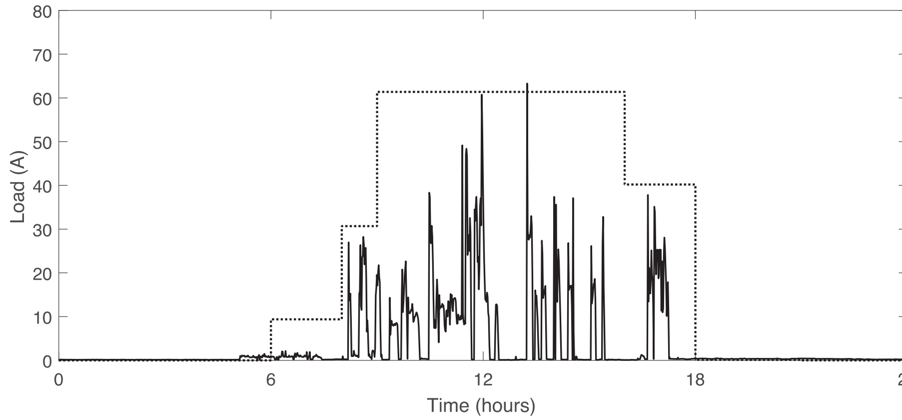

Fig. 3. Load profiles for three SME mini-grid customers with large loads (two mills and one workshop). The measured load profile is shown as a black line. The black line shows each minute's measured average load. The interview-based load profile is shown as a dotted black line.

The system investigated used a flat-rate payment scheme. With a system based on a flat energy tariff, users would likely be more careful about their electricity usage and therefore also be more aware of when appliances were switched on and off. Specifically, users would leave fewer appliances on if they were not considered important. This affects the usage of electricity by night and day. Furthermore, using a flat energy tariff likely increases the usage of low power lightbulbs, and thus reduces the overall load. During the data collection, it was observed that SMEs mostly turned on their appliances when they were needed; they did not leave them on for longer periods unless beneficial. This was especially evident for the large SME loads. For the other SMEs (bars, restaurants, shops etc.), electricity was often used for specific purposes and a change in pricing would likely have limited impact on electricity usage. The change to a flat energy tariff should thus have a relative small impact on SMEs' usage. Household users would likely be more concerned about their electricity use in a system that did not use a flat rate payment scheme. The high night and daily electricity use seen in the household measurements would likely be affected the most. The relatively high day load and lack of high-power appliances (apart from lights) also suggests that appliances are being left on when not in use.

Impacts on mini-grid dimensioning and operation

The calculated performance metrics (capacity factor and load factor) from interview-based load profiles is similar to those in other studies. The load factor values calculated using the interview-based load profiles (0.34–0.53) are similar to those used by Bhattacharyya (2015) (0.14–0.55) in Bangladesh. However, they are 69% lower than the load factors calculated using the measured load profiles. Also, the capacity factor calculated using the interview-based load profiles (0.35) are similar to those reported by The World Bank ESMAP (2007) (0.30) but 50% lower than capacity factors calculated using the measured load profiles (0.54).

The two methods show the smallest differences in the performance metrics for the peak load and coincidence factors and the largest differences for the energy and load factors. The large difference in energy can be linked to the inability of the interview-based load profiles to identify the night and base load for the mini-grid and household, plus the inability to identify running times for the large SME loads. The difficulty in correctly identifying energy use from appliance data was also identified by Blodgett et al. (2017). The energy mismatch for the two methods for a household identified in this study was more than a factor of three, which is considerably higher than the 36% identified by Blodgett et al. (2017). However, when considering energy from the entire mini-grid (on a weekly basis), the discrepancy in energy between the two methods is reduced to about 44%. This reduction is due mainly to the large overestimation of energy in the interview-based load profiles for the large SME loads.

Table 6
Calculated energy values for the measurements and interview-based load profiles for SMEs.

	Measurements	Interviews
Energy (kWh)	60	386
Peak load (A)	63	61
Load factor	0.06	0.37
Coincidence factor	0.67	0.65

The lower energy calculated using the interview-based data can have serious implications on operation. Using a flat energy tariff, an operator's income is proportional to electricity sold. The much lower energy calculated from the interview-based load profiles thus implies that the income would be considerably lower and the overall system less economically viable. The difference in energy also affects the load factor and capacity factor and could have major implications on the dimensioning and operation of mini-grids. This becomes especially important when considering hybrid systems utilising energy storage. Energy storage is expensive and is therefore kept to a minimum level. However, the size of energy storages also depends on evening and night usage. Underestimating energy use thus has major implications for the functioning of such systems, and can result in an inability to supply enough energy.

In terms of generation dimensioning, the peak load from the interview-based load profiles is approximately 81 kW compared to the measured peak load of approximately 91 kW. If the peak load calculated from the interview-based load profiles were to be used for dimensioning, the system would be under-dimensioned by 11%. This could cause improper dimensioning of components and overloading, which can result in damaged equipment. The incorrectly identified peak load also has implications for operation. As the measured peak load is higher than the peak load from the interview-based load profiles, the operator would have to reduce the number of connections in order to avoid overloading. Thus, methodological uncertainties should be taken into account when using interview-based load profiles for mini-grid dimensioning.

The lower energy, load factor and capacity factor have implications for the system's technical and economic performance. A system with a high load factor has lower and/or fewer variations (a flatter load profile) than a system with a lower load factor. Consequently, as generation must to match demand, developing a system with a low load factor is generally more difficult than developing one with a high load factor. Furthermore, systems with high capacity factors utilize a larger share of their capacity than those with low capacity factors. The difference in load factors and capacity factors as calculated from the two sets of load profiles deviate between 34 and 117%. As such the lower load factor and lower capacity factor calculated from the interview-based load profile implies that the system is less technically and economically preferable than shown by the measurements. If load assessments based on interviews are used during the development of mini-grid projects, this could lead to underestimation of technical and economic performance. Mini-grid projects could therefore either be disregarded or suffer problems (and even fail) due to incorrect load assessments.

Improvements of the interview-based data

The issue of interview-based load profiles failing to provide an accurate estimate and therefore also failing to generate accurate performance metrics is linked with a lack of necessary data. It is therefore of great importance to consider how interview-based load profiles can be improved.

The risk of not obtaining the necessary data was a problem on multiple occasions (night load and morning peak). Questions need to be carefully formulated in order to aid in the identification of appliances and their usage patterns. If the interviewer probes for specific usage patterns, it is possible that these will be evident in the results, regardless of whether they actually exist (Powell, Hughes-Scholes, & Sharman, 2012). The interviewer therefore needs to be open to unknown outcomes. Questions thus need to be both specific and general. They need to be specific enough to be able to identify multiple usage times of appliances (such as in the morning and evening). However, they also need to be general enough to reduce interviewer bias or expectations. Therefore, rather than asking, "are there any lights left on during the night?", questions can be focused on the activities. For example, "what are your household members doing in the evening?" Followed by, "does any of these activities require electricity?". This then lead to more detailed questions regarding the appliances and their usage. This process would reduce bias and expectation issues while aiding in identifying usage patterns.

Furthermore, to avoid issues of missing appliances, interviewers should be aware of any regulations or recommendations on the use of certain appliances. In this study, a local individual was used so that a representative sample could be collected during the interviews. This individual was linked to the operator, which could have influenced the likelihood of correctly identifying some types of appliances in the interviews. Thus, it is important to ensure that all members of the interview team are seen as neutral by the interviewees.

If the issues with interview-based load profiles can be dealt with, they have several advantages over measurements. One advantage of load profiles based on interviews is that they are more attainable than measurements. Measurements require special equipment and technical knowledge, which can be expensive and not necessarily available in rural areas. This can decrease access to data and affect reliability if the equipment is not handled correctly. Another advantage of interview-based load profiles is that data is collected on types of appliances and appliance usage. Knowledge of appliances and their usage is important if a local utility aims to implement load management or similar policies aimed at increasing the performance metrics. Methods have recently been proposed for disaggregating load profiles and obtaining information on appliance types and switching behaviour have been proposed (Greenwood, Wade, Davison, & Duby, 2016). This can be used to further improve the accuracy of interview-based load profiles. Similarly, stochastic models using appliance data to improve load profiles resolution and accuracy have recently been proposed (Boait et al., 2015; Mandelli et al., 2016).

Conclusions

This paper has compared load profiles and performance metrics based on interviews and on measurements relating to a rural mini-grid in Tanzania. The study showed distinct differences between load profiles based on interviews and measured data. The differences are mainly seen during the night and in morning usage. Due to the different load profiles generated by the two methods, there are considerable differences amongst the calculated performance metrics. The largest difference was in the calculated energy, which is underestimated by some 48–117% when using interview-based method. This major difference in the calculated energy is also reflected in the load factor and capacity factor, which are underestimated by 34–117% using the interview-based method. However, the estimate of the peak load shows a much smaller error (11%). The performance metrics calculated from the interviews are similar to those reported by other scholars. The large overall differences in the performance metrics could have major implications for the dimensioning and operation of mini-grids.

The differences between the two methods are found to be due to two factors: lack of correct identification of appliances and their usage and lack of coincidence using the interview-based approach. A number of changes to the interview process have been proposed to improve the identification of appliances and usage. The changes include initial questions targeting activities and awareness of regulations.

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