Holistic approach to develop electricity load profiles for rural off-grid communities in sub-Saharan Africa

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Abstract

Providing energy access to remote rural communities in sub-Saharan Africa (SSA) is particularly challenging in areas where grid extension is not a viable option. For these communities, electrification and the fulfillment of the UN SDG 7 can only be achieved effectively by using off-grid electricity supply systems. However, the design process of renewable energy-based mini-grids requires a holistic consideration of all electricity needs, including the electricity demand of commercial customers (productive uses) and public institutions. Furthermore, as electric cooking is increasingly becoming a viable option, each off-grid electrification project should carefully consider to which extend electricity can be used for cooking and water heating, and that consumer preferences might change over time when they experience the advantages of e-cooking devices, which can have a strong influence on the resulting electricity load profile and electricity demand. In this research article we explore the advantages of a holistic hybrid modelling approach, which includes bottom-up and top-down modelling as well as data-driven analyses, for the generation of standard load profiles (SLP) for typical consumers in rural off-grid communities in SSA. Monitoring data from the largest off-grid settlement in Namibia, *Tsumkwe*, is used for data-driven load profile generation as well as for validation within the SLP development process. Finally, the SLP can be added up in order to synthesize customised load profiles for entire off-grid settlements in SSA.

Keywords: Electricity demand assessment, electricity load profiles, standard load profile (SLP), hybrid modelling approach, electric cooking, mini-grid, rural electrification, energy access

1. Introduction

1.1. Background

The United Nations (UN) published their "2030 Agenda for Sustainable Development" in 2015. Sustainable Development Goal (SDG) 7 is intended to ensure access to affordable, reliable, sustainable, and modern energy for all humans, with a special focus on electricity. By 2018, the proportion of the global population with access to electricity reached 90%. As a result, the absolute number of people living without electricity fell below the threshold of one billion. However, the lack of electricity supply primarily affects countries in sub-Saharan Africa (SSA), where 53% of the population have no access to electricity (United Nations, 2020).

Energy poverty disproportionately concerns those living in rural communities in SSA (Louie, 2018). It has a negative impact on different areas of daily life, and the consequences can be severe. For instance, people's health is affected by air pollution when using traditional biomass for cooking and heating in inappropriate stoves. Lacking access to modern energy also reduces education and income opportunities, and is a driver for gender inequality (Bhatia and Angelou, 2015; Louie, 2018). Furthermore, lack of access to electricity prevents people from using radio, television, and internet, which results in a lack of information and makes rural areas even more isolated (Louie, 2018). To summarize, access to clean energy is essential for human, social, and economic development.

1.2. Rural electrification through solar-based mini-grids

Many studies have shown that grid connection is not feasible for a large part of remote rural communities in SSA. Hence, rural electrification via renewable energy-based off-grid electricity supply systems is required to achieve the UN SDG 7 (IEA, 2019; Williams et al., 2019; Lorenzoni et al., 2020; Scott and Coley, 2021). For most remote settlements in SSA, mini-grids based on PV are the preferred technical solution for access to

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electricity due to the high and relatively consistent solar irradiation levels in these regions. Solar-based mini-grids generally consist of PV modules for electricity generation, a battery energy storage system, inverters, a control/management system, and an electricity distribution system. If further electricity generators are present, e.g. wind turbines or a diesel generator, the system configuration is called a solar-hybrid mini-grid. In contrast to individual solar home systems (SHS), mini-grids can provide entire communities with a high-quality electricity supply, that is comparable to the national grid and allows for the use of powerful three-phase AC appliances. Hence, mini-grids offer great opportunities for sustained economic and social development by enabling extensive commercial activities (productive use of electricity) and effective public infrastructures and services.

Although being the least-cost option for many rural communities, isolated mini-grids naturally imply higher electricity costs for consumers compared to users that are supplied via the national electricity grid (Kühnel et al., 2020). Therefore, any off-grid electricity supply system requires a thorough planning process, including careful holistic consideration of the electricity demand of the community it is intended to serve (Williams et al., 2019; Scott and Coley, 2021). Anticipated load profiles for isolated rural communities are a critical resource in the mini-grid design process (Prinsloo et al., 2018). Therefore, the objectives of this research article are to analyse the electricity needs of rural off-grid communities in SSA, and to present a holistic procedure to generate standard electricity load profiles for typical consumers in these settlements as well as realistic load profiles for entire communities.

2. Literature review

2.1. Energy demand vs. electricity demand in remote rural communities

The energy demand of a rural community can basically be divided into three categories (Mandelli et al., 2016): energy for household basic needs, energy for community services , and energy for productive uses devoted to income generating activities.

Tab. 1: Categories of energy demand in remote rural communities (cf. Mandelli et al. (2016))

Energy for community services	Energy for households	Energy for productive uses
Water supply, Education, Healthcare, Street lighting Mobile network, TV/Radio broadcasting Public institutions (e.g. Community centre)	Lighting Electrical appliances Space cooling and heating Cooking and water heating	Irrigation, Agriculture, Crop processing Micro market, Snack bar, Barbershop, Tourism

As outlined in Tab. 1, each of these categories consists of a variety of very different consumers with distinct and diverse energy consumption patterns, resulting in a complex composition of the community energy demand. It is important to point out here that this energy demand will only partly be covered by electricity, while other sources of energy also play a significant role in most rural communities. For example, the energy service of ‘cooking and water heating’ can be provided by either non-electrical appliances (such as gas burners, solar cookers, or traditional biomass cooking stoves) or by electrical appliances like hotplates and kettles. Hence, the usage patterns of (non-) electrical heating and cooking devices have a profound influence on the resulting electricity demand and electricity load profile of the respective community and, thus, need to be considered carefully (Prinsloo et al., 2016; Scott and Coley, 2021).

For example, a survey conducted by Lloyd and Cowan (2004) in an informal settlement in South Africa revealed that the average monthly energy consumption for rural households cooking with electricity is 210 kWh, compared to 150 kWh for households without electrical cooking (Prinsloo et al., 2016). A recent “feasibility study to pave the way for mass distribution of electric hotplates to rural households in Malawi” found that electric cooking accounts for about 40% of the total household electricity consumption for a middle-frequency user (approx. 50 cooking events per month), and even 79% for a high-frequency user with approx. 75 cooking events per month. These results are all the more remarkable as only one hotplate of 1,500 W was provided to the participating households, and an accompanying survey showed that this hotplate “was too small to cook all the food for a household” so that “a fire was kept going for cooking purposes as well”. The average daily hotplate consumption was found to be 1.14 kWh/d. On average, each electrical cooking event consumed 0.53 kWh and lasted for 44 minutes (Access to Energy Institute, 2021).

2.2. Determination of electricity demand and electricity load profiles for rural communities in SSA

Many research articles point out that there are major challenges and uncertainties in the assessment of the electricity demand of isolated rural settlements, especially the high variability of demand and a general lack of reliable and accessible monitoring data from existing electrification projects (Prinsloo et al., 2018; Kühnel et al., 2020; Lorenzoni et al., 2020). To address these challenges and support the planning and design process of mini-grid systems, increasing research efforts have been made in recent years concerning the electricity demand, electricity load profiles, and load forecasting for rural off-grid communities in SSA and other developing countries.

Lorenzoni et al. (2020) created a database with real-world load profiles from 61 mini-grids in the global south, which is based on primary (fieldworks) and secondary (private developers, literature) data, to provide an open dataset for researchers and practitioners. After having developed a representative daily load profile for each of these settlements, these profiles were normalised to the mean hourly demand, and grouped according to similarities in their course and duration curve. A data-driven analysis performed on the profiles revealed five "archetypal load profile clusters" and four reference load profile shapes for mini-grids. Subsequently, correlations were explored between these load profile shapes, the electricity consumption, and external factors that characterise the communities, including technical, socio-economic and geographical parameters. Nevertheless, the authors consider their database and classification of load profiles only as a first step towards a comprehensive understanding of archetypal load shapes. They call for an extension of the open dataset and for further studies to assess the load demand of off-grid communities, its evolution over time, and its correlations with further community characterisation factors (Lorenzoni et al., 2020).

Kühnel et al. (2020) also emphasise the difficulties to estimate the electricity demand and load patterns of un-electrified rural off-grid communities, and criticise the absence of a database with standard load profiles for initial electrification. The authors highlight large discrepancies between survey results (before electrification) and later consumption measurements of up to 300%, and advocate the use of data-driven load profiles for future mini-grid electrification projects. In order to create a database for this purpose, and to generate reference load profiles, Kühnel et al. (2020) suggest to develop a monitoring and evaluation framework (MEF) that collects data from mini-grid operation, and makes them available on an open-source basis to all interested stakeholders. The paper also describes and analyses in detail how the electricity demand of recently electrified settlements grows over time due to economic development, leading to immigration and increased individual consumption. However, neither commercial customers nor public infrastructures are considered in the study.

Literature review also revealed that the electricity demand for cooking and water heating is usually not (explicitly) considered in the demand assessment for mini-grid systems, despite its immense importance (see chapter 2.1). However, electric cooking is rapidly becoming a viable solution in rural off-grid areas that are powered by mini-grids, due to significant decreases in both PV and battery prices (Couture et al., 2019). Hence, the interplay between mini-grids and electric cooking has recently gained increased attention. For example, Lombardi et al. (2019) conducted an assessment of the techno-economic potential of a fully-renewable solar mini-grid for electricity load and electric cooking in community and household applications. Keddar et al. (2020) analyse the optimal sizing of mini-grids that are able to accommodate new e-cooking demand.

2.3. Generation of electricity load profiles for typical consumers in rural communities in SSA

In a scoping exercise, Prinsloo et al. (2016) identified hourly reference load profiles for both electric and thermal energy demand for typical homesteads in isolated rural African villages. These profiles are made available as a digital timeseries and can be fed directly into standard simulation software. However, this study makes the simplified assumption that a single homestead has the same archetypal reference shape like an entire village, which means that the influence of balancing effects was completely neglected.

Scott and Coley (2021) characterise household demands based on consumption and customer data of two mini-grids in Tanzania. Patterns of use are analysed by examining the electrical equipment owned and the demography of supplied households. The authors identified four distinct use patterns, but also illustrate that a connection between these, the device possession and its use as well as the socio-economic status is complex to identify and call for further research.

Li et al. (2018) from the National Renewable Energy Laboratory (NREL) developed a tool named Microgrid Load Profile Explorer that allows researchers to synthesize load profiles for households and commercial users in SSA. However, the tool lacks flexibility, for example, it is based on seven appliances which are assumed to be the same for all types of households. Also, the time of energy consumption is pre-defined in the tool and there is no provision to alter it. Other shortcomings are that all types of households show a similar electricity consumption pattern, and a similar consumption trend on weekdays and weekends.

A recent study from Asuamah et al. (2021) presents a large set of daily load curves that are developed on the basis of a survey analysis. The estimation of energy demand is categorised into three areas (residential users, commercial users, and street lighting), with the residential users being sub-classified in low-, middle- and high-class users. Similarly, the commercial load is differentiated into small-, medium and high-scale users.

2.4. Electricity load profile modelling approaches

A comprehensive review of 32 residential electricity load profile models and the underlying modelling techniques is given in Proedrou (2021). At present, load profile models are typically categorised as top-down and bottom-up models. However, in recent years new models have been developed that do not fit into either category as they combine methods and elements of both the top-down and bottom-up approaches. Consequently, Proedrou (2021) proposes to introduce a new sub-category of "hybrid models" for this novel modelling approach.

Besides the basic modelling technique, electricity load profile models can also be classified according to their primary intended application. As there is no generally accepted classification scheme, Proedrou (2021) suggests a division into three areas of application: (a) demand side management (DSM), (b) planning, control and design of energy systems, distributions grids and local energy efficiency strategies (PCD), and (c) residential load profiles (RLP). Furthermore, load profile models can be differentiated based on their sampling rate – low-resolution models (15 minutes to 1 hour), middle-resolution models and high-resolution models (sampling rate of at least 1 minute) – as well as based on the main statistical methods that are used in the modelling process: Markov chain models, probabilistic models, and Monte Carlo models (Proedrou, 2021).

However, the 32 residential electricity load profile models reviewed in Proedrou (2021) cannot be used for the purpose of this research article – the development of standard electricity load profiles for typical consumers and entire off-grid settlements in rural SSA – as these models are tailored to the residential sector in developed countries and require input data that is not available for rural communities in SSA. Also, the 30 publicly available residential load profiles, that are presented in Proedrou (2021), do not apply to the aforementioned objective as these existing datasets refer to developed countries or, in case of the "Indian data for Ambient Water and Electricity Sensing" (iAWE), to a three-storey home in the city of Delhi (Batra et al., 2013).

3. Holistic approach to generate standard electricity load profiles for typical consumers in rural off-grid communities in SSA

The extensive literature review revealed that there is no standardised method for assessing the electricity demand and electricity load profiles, respectively, of rural off-grid settlements in SSA. Load assessment remains a complex task, which is particularly critical for currently un-electrified communities. However, existing mini-grids are also continuously exposed to on-going changes of electricity demand, be it through demographic changes, or due to the adoption of new technologies such as electric cooking and water heating, and potentially also electric vehicles. In particular, the electricity demand for cooking and water heating is not (adequately) considered in many load profiling models and tools, although it can have a very significant influence on the community load profile already today, and will become even more important in the future.

In conclusion, all existing approaches to anticipate the load characteristics of rural communities in SSA, that are known to the authors, have shortcomings in one way or another. Therefore, this paper aims to contribute to reducing this information gap by presenting a holistic procedure for the development of standard load profiles (SLP) for typical consumers in rural off-grid settlements in SSA. In this research article, the term 'SLP' refers to a load profile that represents the average electricity demand curve of a specific consumer type, similar to the well-known H0 SLP for European households (cf. Proedrou (2021)). The fundamental advantage of SLP is their additivity, i.e. their suitability to be added up directly in order to determine the load profile of a group of consumers or an entire community.

The ultimate goal is to model the electricity load profile of entire off-grid settlements that are currently unelectrified. For this purpose, validated SLP are combined with information about the structural composition of the target community: structural data, such as the number of households and information about the public infrastructure, are used to determine a set of SLP that represent this specific settlement as a whole. Finally, these SLP are added up to the settlement load profile, which in turn can be used to custom design a mini-grid.

To achieve these goals, a holistic hybrid load profile modelling approach is proposed in this study. As shown in Fig. 1, we suggest to combine bottom-up and top-down modelling as well as data-driven load profile generation techniques, in order to compute generally applicable SLP for typical consumers in rural off-grid communities in SSA. According to the classification of load profile models proposed by Proedrou (2021), our modelling approach can be characterised as a hybrid low-resolution model for the purpose of PCD (planning, control and design of energy systems and distributions grids) and using probabilistic statistics (see section 2.4).

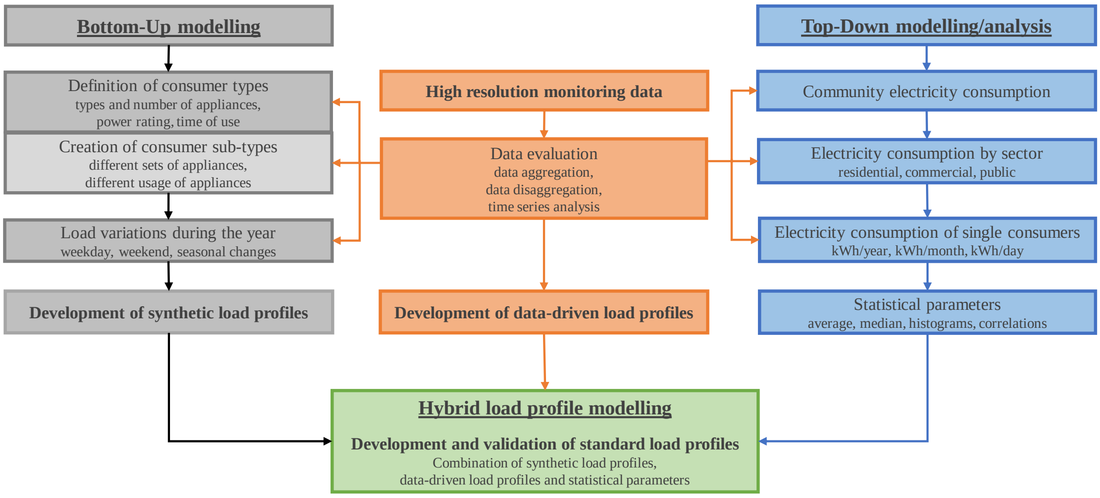

Fig. 1: Holistic approach for the development of standard load profiles for rural off-grid communities in SSA

3.1. Bottom-up modelling

A general description of the bottom-up modelling method to develop household load profiles is given in Proedrou (2021) and Gao et al. (2018). In this paper, the bottom-up modelling process starts with the definition of consumer types as indicated in Fig. 1. Every consumer type is characterized by a set of electrical appliances – including the type, quantity, and power rating of each appliance – and the typical usage pattern (operating times) of these appliances. Typical examples for consumer types from the residential, commercial, and public sectors are a middle-income household, a snack bar, and a primary school.

Subsequently, sub-types are created in order to generate a large set of electricity load profiles for each consumer type. Different consumer sub-types account for differences in the use of electrical appliances (different user behaviours). They also allow for modelling slight variations in appliance possession, for example, a small household is likely to have fewer lights and mobile chargers than a large household of the same income level. The effects of the creation of consumer sub-types are demonstrated in more detail in section 4.1. Furthermore, for the majority of consumers, it is not sufficient to develop a general set of daily load profiles. Instead, there are regular load variations that occur in the course of the year. Most important for most consumer types are the changes between weekdays and weekend days. Therefore, specific load profiles are generated for weekend days – in some cases it is also necessary to differentiate between Saturday and Sunday – which finally allow the construction of weekly load profiles.

Moreover, some consumer types require a careful consideration of seasonal variations. For example, the cooling demand (during sunshine hours) and the heating demand (during night hours) of households can change considerably in the course of the year. In rural Namibia, the electricity use for cooking is much higher on rainy days compared to dry and sunny days, on which traditional cooking with biomass is preferred. Last but not least, the recurring changes between school periods and holiday periods result in extreme differences for the daily electricity demand of any school.

The result from our bottom-up modelling procedure is a set of synthetic load profiles for each consumer type, which cover a large range of user behaviours and differences in appliance possession, as well as changes in electricity demand in the course of the year. The great benefit of synthetic load profiles is that they indicate the peak load of a consumer. As shown in Fig. 1, the synthetic load profiles are fed into the hybrid load profile model in order to be validated and transformed into SLP.

3.2. Data-driven load profile generation

As described in sections 2.2 and 2.3, the availability of monitoring data from rural electrification projects in SSA has increased in recent years. This treasure trove of data is increasingly being analysed by researchers, and used to generate data-driven load profiles and for load forecasting. In the future, if high-resolution measurement data will become available as well, also highly sophisticated methods of data analysis could be applied, such as time series analysis, load disaggregation via non-intrusive load monitoring (NILM), and machine learning. The data-driven approach can also be combined with bottom-up modelling for the purpose of electric load forecasting (Ye et al., 2019), and provide valuable input for top-down modelling and the top-down analysis of measurement data (see Fig. 1).

3.3. Top-down modelling and top-down analysis

Top-down models use historical data at an aggregate level and/or statistical parameters “to derive relationships between them and the electricity consumption” (Proedrou, 2021). For this reason, these models are also referred to as statistical models (Gao et al., 2018), and the data-driven classification and load profile modelling approach proposed by Lorenzoni et al. (2020), using characterisation factors, falls under this category.

A basic principle of top-down analysis is to break down aggregated data into sub-categories, and into shorter time periods. For example, in the first step, the electricity consumption at community level can be sub-divided into the main consumption sectors of an off-grid community: the residential, commercial and public sector (cf. Fig. 1 and Tab. 1). Similarly, the annual electricity consumption can be disaggregated into the electricity consumption per month. This step makes it possible to examine the seasonal variations of the electricity demand of a particular community, and to relate them with the seasonal changes in the availability of renewable energy resources (e.g. solar irradiation) in this settlement.

In the next step, if sufficient information is available, the electricity demand is further divided into groups of consumers (e.g. a district/neighbourhood), and finally into single consumers. When the monthly electricity consumption is broken down further into daily consumption figures, recurring changes in the course of the week can be detected and incorporated into the top-down model (e.g. weekday-to-weekend variation). The daily consumption figures – or even hourly values – might be obtained directly from a monitoring system or from aggregating high-resolution monitoring data (see Fig. 1).

Finally, the electricity consumption figures can be evaluated statistically in order to recognise and quantify major correlations and influencing factors. Further insights are gained by calculating statistical parameters such as the average or median daily/weekly/monthly electricity consumption of the households in a settlement. These statistical key figures are also a valuable input for the development and validation of SLP in hybrid load profile modelling (see Fig. 1). Last but not least, histograms and other statistical diagrams can provide a deeper understanding of the electricity demand structure in a particular community in SSA.

3.4. Hybrid load profile modelling

In general, the hybrid load profile modelling approach is a combination of bottom-up and top-down modelling (Proedrou, 2021). However, due to the general shortage of reliable information and measurement data from off-grid settlements in SSA, we propose to combine all available pieces of information in a holistic hybrid modelling procedure (see Fig. 1). This includes a comprehensive set of synthetic and data-driven load profiles, as well as electricity consumption figures and statistical parameters from top-down analysis and literature (e.g. energy statistics and real-world monitoring data). In an iterative process, the raw load profiles are validated and SLP are developed for typical consumer types in remote rural communities in SSA.

This validation includes a check and calibration of the (raw) synthetic load profiles with verified electricity consumption figures (e.g. kWh/d). After validation, the resulting load profiles (which are meant to represent the *course of electric load of an individual consumer* as accurately as possible) are transformed into SLP, which are intended to represent the *average expected load curve for a large number of consumers* of the respective consumer type.

Hence, SLP are intended to be additive and generally applicable for load assessment and load forecasting. SLP cover the same amount of electricity (in kWh/d) as individual load profiles, but have a strongly smoothed curve shape. Furthermore, while individual profiles show the true height and width of consumption peaks, SLP have significantly flatter and wider peaks.

4. Results and discussion

In this section, the development of synthetic load profiles and data-driven load profiles is demonstrated at the example of *Tsumkwe*, a rural off-grid settlement in the Otjozondjupa region in the north-east of Namibia. *Tsumkwe* has the largest solar-hybrid mini-grid system in Namibia and is analysed as one of the case studies within the *PROCEED* research project[1]. The *Tsumkwe Energy Project (TEP)* was initiated in 2011 and transformed the existing diesel-powered mini-grid into a solar-diesel hybrid mini-grid. Besides the integration of a PV plant and a battery bank into the electricity supply system, the *TEP* also introduced extensive electricity saving measures in the settlement of *Tsumkwe*: electric water heaters and electric stoves were replaced by solar water heaters and LPG stoves, and inefficient incandescent lights were exchanged for energy saving lights.

4.1. Bottom-up modelling: Household load profiles

In this study, the households of a rural community are categorized into three consumer types: (i) low-income, (ii) middle-income, and (iii) high-income households. As described in section 3.1, each of these household types is characterized by a representative set of electrical appliances and their typical times of use.

In order to consider the differences in appliance possession and appliance usage patterns within a specific consumer type, each household type is further divided into different household sub-types. For example, we differentiate into small (1-5 persons), medium (6-10 persons), and large (>10 persons) households. For each of these sub-types, Tab. 2 shows the respective set of appliances that are typically used by a middle-income household in a Namibian rural off-grid settlement such as *Tsumkwe*. This information is based on surveys and observations from research stays within the *PROCEED* project, and was cross-checked by the *Namibia Energy Institute* and engineers from *DIS Engineering*, a solar company that has recently implemented a solar PV installation in *Tsumkwe*.

Tab. 2: Typical sets of electrical appliances for middle-income households of different sizes in *Tsumkwe*

Appliance	Power rating	Quantity		
	Watts	1-5 persons	6-10 persons	10+ persons
CFL Bulb	8-12	2	4	6
Mobile Phone Charger	10-15	2	3	4
Radio	10	1	1	2
TV	150	1	1	1
Satellite Dish + Decoder	40	1	1	1
DVD Player	20	1	1	1
Small Fridge	250	1	1	1
Laptop	65	-	-	1
Electric Hot Plates	1000	2	2	4

[1] **P**athway to **R**enewable **O**ff-Grid **C**ommunity **E**n**e**rgy for **D**evelopment. https://www.bmbf-client.de/en/projects/proceed

In the following, we demonstrate the bottom-up modelling procedure and present preliminary results for a medium-sized (6-10 persons) middle-income household. Fig. 2 shows the preliminary synthetic load profile of this household sub-type for a working day with electrical cooking. Although the residents in rural off-grid communities generally use relatively old and inefficient electrical appliances, the load profile is dominated by the electricity demand of the hot plates. If cooking is not done electrically, the load profile is dominated by the fridge and the TV. When different household sizes are compared, the most noticeable difference on days with electrical cooking is the almost doubled peak load for large households due to the double number of electric hot plates.

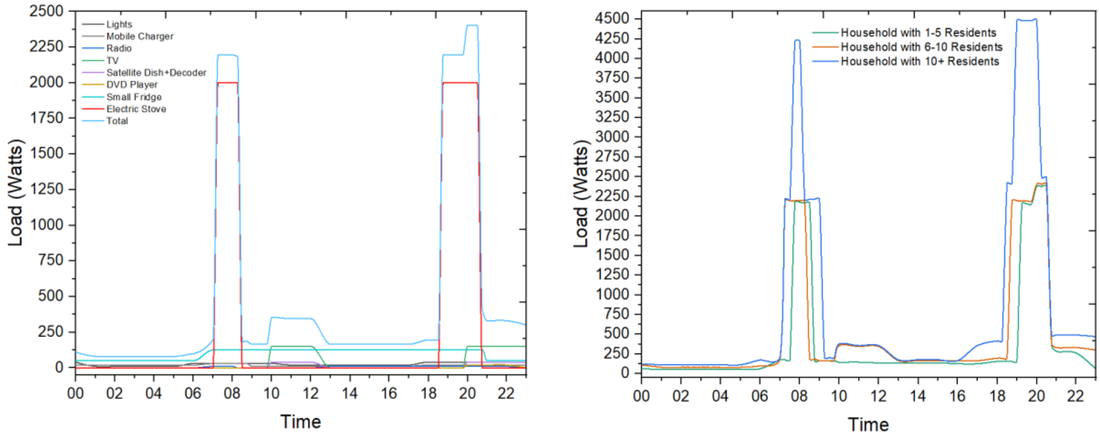

Fig. 2: Preliminary synthetic load profile of a medium-sized (6-10 persons) middle-income household in *Tsumkwe* with electrical cooking on a working day (left). Comparison of synthetic load profiles of middle-income households of different sizes (right)

In reality, even households with the same number of residents and an identical set of appliances will use their electrical appliances in a different way. Moreover, even in a specific household the time and duration of appliance use differ from day to day. In order to deal with these variations in user behaviour, which represent a major uncertainty in bottom-up modelling, three different load profiles for each consumer sub-type are generated: besides the profiles presented in Fig. 2, which refer to an average appliance use, we also generate a profile for a lower usage and a profile for higher appliance usage, respectively. This procedure results in a range in which the electric load can be expected (see Fig. 3). This increase in variety and flexibility is also a benefit for subsequent modelling steps, namely for the validation of synthetic load profiles and the development of SLP (see Fig. 1). Fig. 3 also shows the differences in electric load between weekdays and weekend days. On the weekend, a typical household has a shifted morning peak and a higher electricity demand during the afternoon and evening hours.

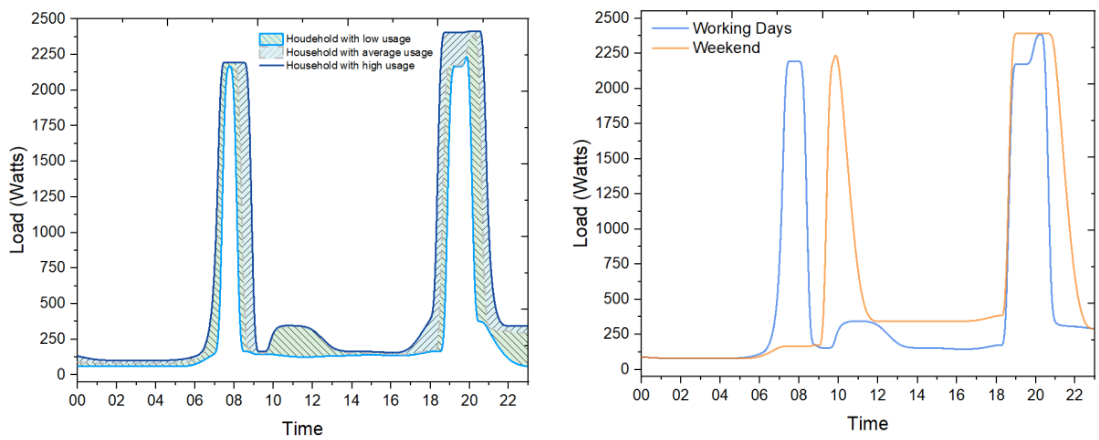

Fig. 3: Assumed variations on the synthetic load profile of a medium-sized middle-income household with electrical cooking in *Tsumkwe* due to different intensities of appliance usage (left) and the weekend effect (right)

Fig. 4 shows the full range of electrical load that is expected, under the assumptions made in this study, for a middle-income household in a rural off-grid settlement on a working day if electric cooking is used. The lower boundary of this range is formed by the synthetic load profile of a small (1-5 persons) household, which has a lower appliance use than the average 1-5-person household. Similarly, on the upper side, the range is limited by a large household (more than 10 members), which uses more electricity than other households of this size, including a third meal that is prepared on the electric hot plates during noon hours.

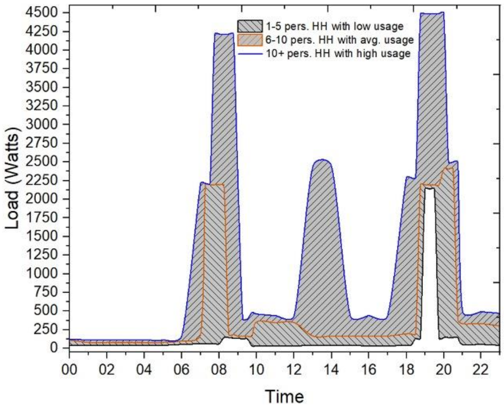

Fig. 4: Full range of electric loads (grey area) that is covered by the synthetic load profiles for all sub-types of a middle-income household with electrical cooking on a workday in a rural off-grid settlement such as *Tsumkwe*

4.2. Data-driven load profile generation: Electricity load profiles of a boarding school

In this section, the development of data-driven load profiles is demonstrated at the example of the secondary school in *Tsumkwe*. This school is a boarding school complex and consists of the classroom building, a boarding home for students (including a kitchen and a cold storage room), and teachers' houses. For the school complex as a whole, there are monitoring data available for the entire year 2020 as shown in Fig. 5. This dataset was collected within the *PROCEED* project and represents 15-minute averages of the electric load (or: power consumption).

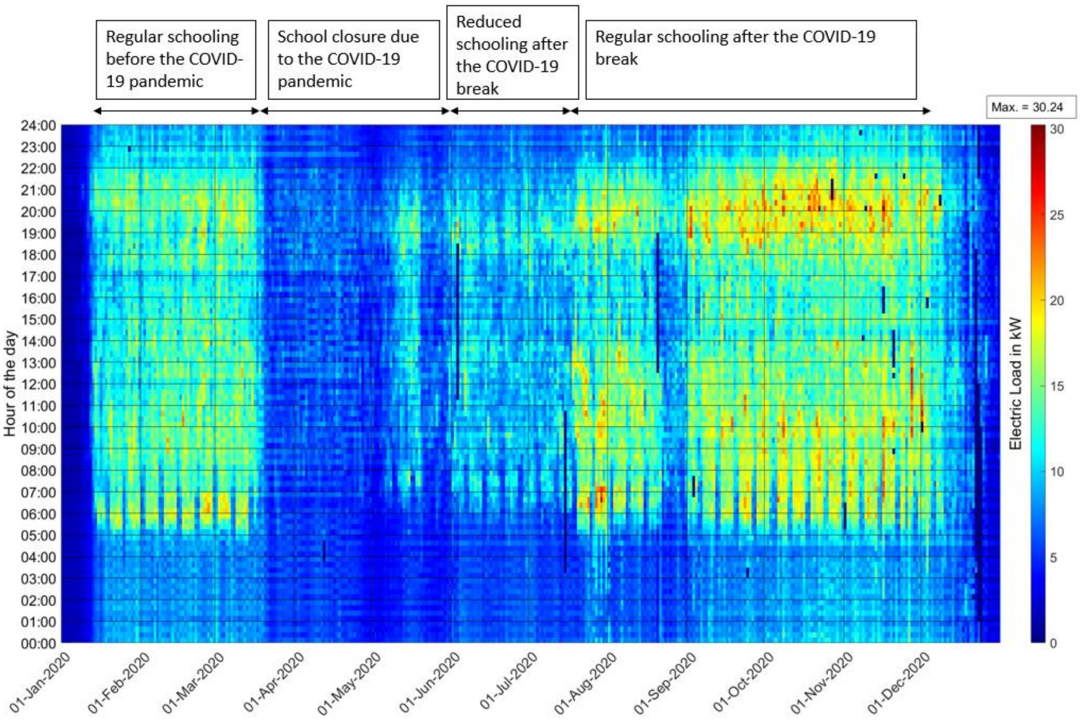

Fig. 5: Electric load patterns of the secondary school complex in *Tsumkwe*

As a first step of load profile development, the year 2020 is divided into four characteristic periods of school operation as shown in Fig. 5 (the first days and the last days of the year, which are not assigned to any period, are the summer holidays). Subsequently, each of these periods is evaluated individually in order to generate meaningful data-driven load profiles that are representative for specific modes of school operation. Also within each period, we carefully select a representative data set for evaluation. For example, when computing the load profile of a typical school day (cf. Fig. 6), the weekend days are removed from the data set in a first step. Secondly, every public holiday is excluded from the representative data set of school days, and data gaps are eliminated.

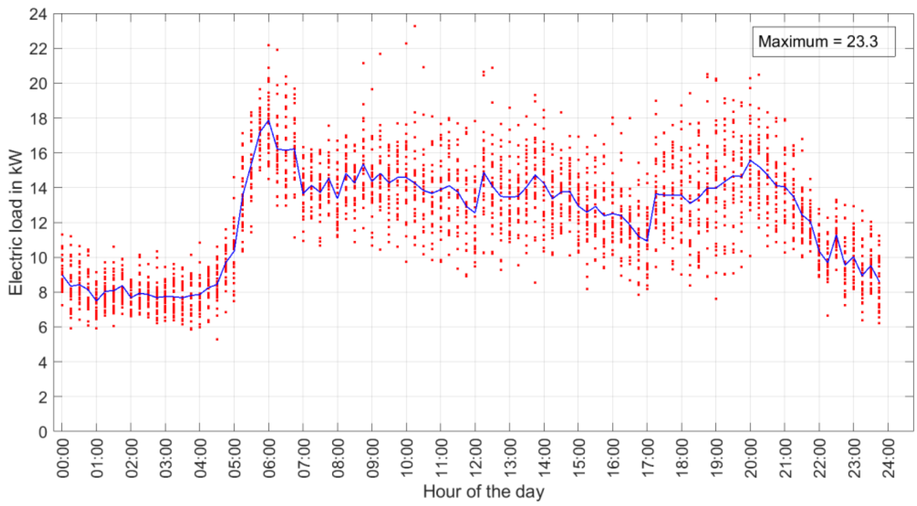

Fig. 6: Electricity load profile of the secondary school complex in *Tsumkwe* on a school day (regular schooling before the COVID-19 pandemic)

Fig. 6 shows the final representative dataset, which was used to compute a representative data-driven load profile for school days of the regular schooling period in 2020 before the COVID-19 pandemic, with each red dot representing a measured 15-min average electric load of the *Tsumkwe* secondary school complex. This specific data set contains all workdays (Monday to Friday) from 03-02-2020 to 13-03-2020, i.e. 30 days of regular school operation. Finally, the mean value is calculated from all load values with the same timestamp. This results in four average electric load values for each hour of the day, which are plotted as the blue line in Fig. 6 and represent the data-driven school day load profile of the aforementioned period.

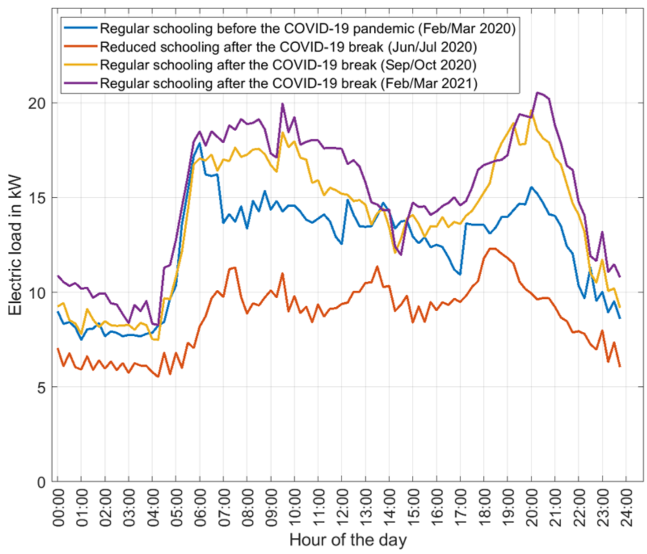

Fig. 7: Electricity load profiles of the secondary school complex in *Tsumkwe*

Fig. 7 shows the data-driven load profiles of all three major schooling periods that are indicated in Fig. 5, together with a data-driven load profile derived from the regular school days in February/March 2021. It is noticeable that the average electric load and, thus, electricity consumption is significantly higher after the COVID-19 break and the subsequent reduced schooling phase, than before the COVID-19 upheavals. Secondly, the load profiles presented in Fig. 7, together with on-site information from *Tsumkwe*, indicate that thermal needs primarily shape the load profiles of the school complex: the particularly high electric loads measured in the evening hours can primarily be attributed to the teachers' cooking activities, the prominent morning peak in the regular schooling period before the COVID-19 break occurs mainly due to the preparation of breakfast, and the high baseload at night is mainly caused by the cold storage room. Last but not least, the electricity load profile derived from the period of reduced schooling after the COVID-19 break (depicted in red in Fig. 7), is characteristic for a non-boarding school without breakfast preparation before school starts.

4.3. Top-down modelling: Electricity consumption by sector

As outlined in section 3.3 and Fig. 1, the first step of top-down modelling is to disaggregate the overall electricity consumption of an off-grid community into the main consumption sectors: the residential, commercial, and public sector. For the settlement of *Tsumkwe*, this breakdown is performed based on the energy sales report 2020/21 (July 2020 - June 2021), which was made available by the local mini-grid operator *CENORED* (*Central North Regional Electricity Distributor*):

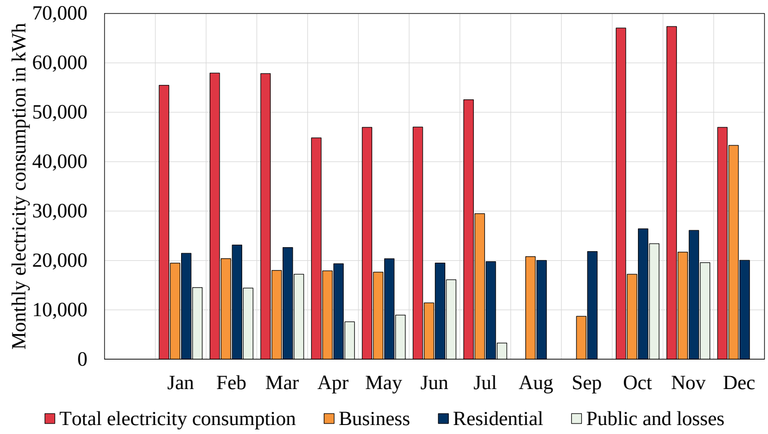

Fig. 8: Disaggregation of the total electricity consumption of the *Tsumkwe* settlement into the main consumption sectors (preliminary results)

However, the results shown in Fig. 8 need to be regarded as preliminary results and treated with caution, due to three reasons: (i) the data set is incomplete (August, September), (ii) the exact distinction between the business sector and the public sector is unclear, and (iii) the underlying accounting period was strongly influenced by the COVID-19 pandemic. Therefore, the breakdown into consumption sectors shown in Fig. 8 still needs to be validated and is primarily intended to illustrate the top-down analysis approach in general.

5. Conclusions and Outlook

Solar-based mini-grids can make an essential and effective contribution to achieving universal access to electricity as formulated in UN’s SDG 7. However, reliable electricity load profiles remain a critical resource for the proper design of mini-grids for un-electrified rural communities in SSA. As a contribution to reduce this information gap, our article proposes a holistic approach to develop standard load profiles (SLP) for typical consumers, and to forecast electric load profiles for entire off-grid settlements of different sizes and structures. These load profiles are intended to simplify and accelerate the design process for new mini-grids, by dispensing with detailed and time-consuming on-site surveys.

The term ‘holistic’ has a threefold meaning in this paper, referring to (i) the integration of all available pieces of information from bottom-up and top-down modelling as well as data-driven analyses, (ii) an explicit consideration of the electricity demand of productive uses (commercial sector) and community services (public sector), and (iii) a careful consideration of the thermal energy needs, which can be provided either by electrical or by non-electrical devices (e.g. gas burners, solar thermal systems, solar cookers, and traditional biomass stoves).

The question whether – and to which extent – electrical appliances are used for cooking, water heating/boiling and cooling has a strong influence on the electricity load profile and the resulting electricity demand, both at individual consumer level and community level. In rural Namibia, the actual use of electrical devices for thermal services heavily depends on the current weather conditions. For example, electrical hot plates and kettles are used more likely and more intensively on rainy days because the use of wood burning stoves and solar-based devices is considerably lower on these days. As the increased electricity consumption for thermal services overcompensates the reduced use of electrical cooling devices (mainly fans), the electricity demand is especially high on rainy days with a particularly low solar radiation supply. Nevertheless, the influence of thermal needs, and of electrical appliances to meet these needs, is usually not addressed in the literature on electricity load profiles and electricity demand assessment in the context of rural off-grid settlements in SSA.

As highlighted in Kühnel et al. (2020), especially renewable energy-based mini-grids are vulnerable to growing electricity demand over time. Therefore, a holistic modelling approach should also allow for modelling the evolution of electricity demand due to a growing population and increased individual demand. For the modelling procedure proposed in this study, this basic requirement is ensured by the fact that settlement load profiles can be synthesized from SLP of individual consumers. Hence, the number of SLP can be easily increased in order to represent an enlarged community. Secondly, growing individual demand (due to greater appliance possession and/or more intensive appliance use) can be considered either by adapting the SLP of the respective consumers, or by creating new SLP for new consumer types.

This modularity and adaptability are key advantages over the approaches presented in section 2.2, which model the settlement load profile as a whole (cf. the concept of "archetypal profiles" in Lorenzoni et al. (2020)). The inherent flexibility of our holistic modelling approach also allows investigating the influence of new consumers on the settlement load profile, e.g. the connection of new households to the mini-grid, the opening of new businesses, or the purchase of new electrical consumers such as electric vehicles, which increasingly plays a role in electrified rural off-grid communities. Also, potentially changing practices regarding the use of electrical appliances for cooking and water heating can have a major impact on the evolution of the electricity demand of an electrified community, and should therefore be examined more closely.

Based on the holistic modelling approach described in this research article, SLP need to be developed for typical consumer types in rural off-grid communities in SSA. For the validation step within the SLP development process, current monitoring data is available for selected consumers in the mini-grid settlements of *Tsumkwe* and *Gam*, including different types of households, a clinic, a lodge, and a police station. For both mini-grid communities, which are located in the Otjozondjupa region in the north-east of Namibia, further on-site information is available, such as socio-geographical and socio-economic data, including survey results. The validated SLP will be made publicly available in an online database to the research community and to practitioners working in the field of mini-grid planning and development. This tool is expected to facilitate the generation of customised load profiles for off-grid settlements in SSA.

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