Smart Village Load Planning Simulations in Support of Digital Energy Management for Off-grid Rural Community Microgrids

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Abstract

In isolated rural village electrification, renewable energy resources are often the only alternative to provide sustainable energy to economically deprived isolated rural communities. In support of current alternative energy system developments, engineers use smart village based computer model design approaches. This includes desktop computer simulation modelling for renewable energy systems and smartgrid energy management systems to plan and scope village energy projects for particular technology configurations. This approach also supports design site component option appraisals before physical installation at targeted pilot sites. Disaggregated demand load data from advanced metering infrastructure is however hardly available to assist with the technical planning and design optimization for planned rural energy systems at remote rural villages. This means that logical demand load profiles for traditional rural villages have to be computer simulated. In this paper we describe the basic principles around discrete time device disaggregated rural village electrical load profile simulations suitable for experimentation with smart microgrid design, economic optimization and critical demand response analysis. The engineering simulation model incorporates physical appliance energy ratings and device-use behaviour patterns as basis for synthesising disaggregated archetypal load profiles. The simulated disaggregated load category archetypes reflect realistic disaggregated energy consumption patterns for devices in typical isolated rural villages. Computer generated rural village load time-series datasets are output in formats suitable for demand load data direct exports and imports into custom or commercial energy modelling software simulation platforms such as TRNSYS, HomerEnergy, EnergyPlan and

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EnergyPlus. The simulated rural village demand load data can thus be used to validate numerical simulation models for newly planned smart rural village energy systems, or experimentation with economic optimization and demand response for multi-priority load control in rural smart microgrid environments.

Keywords: Smart rural village; Cyber physical systems; Discrete time simulation; Off-grid energy systems; Demand response; Disaggregated load profile; Rural electrification

1. INTRODUCTION

A substantial proportion of the world's population lives in geographically isolated rural areas. Sparsely populated regions are often unable to justify grid infrastructure extensions to their areas because of the economical distance limit and low economic income potential for centralised electricity grid infrastructure. While many deprived rural households and villages in such areas are still without power or electrical grid infrastructure, these disparate communities have an equal right to equitable access for energy towards economic development [1]. The situation necessitates the need for the provision of village power to small off-grid rural village communities through a means other than through utility grid extension [2].

The IEEE smart village concept offers a basis for technology development through ideas aimed at the design of new grass-roots level micro-utilities able to act as catalyst for rural development. This smart village approach supports rural village community development in a bottom-up approach, through sustainable energy system ideas based community shared renewable microgrid technology [3]. Other development organizations such as the Alliance for Rural Electrification (ARE) also assists developing countries in efforts to reduce energy poverty. Their support similarly aims at the design and development of cost-effective small-scale renewable energy solutions able to provide optimal energy performance within the physical and socio-economic reality of rural areas [4].

In support of such initiatives, engineering modelling and design approaches have been used in rural electrification planning [5]. Computer aided modelling and design processes has the advantage that it can determine power generation and microgrid system behaviour for particular pilot design sites, before the physical systems are rolled out in the field [6]. Modelling design approaches also use desktop computer simulation models for shared renewable energy systems in community microgrid configurations, mainly to optimize and evaluate the suitability of a particular technology in advance [7]. In the utility power market, technologists also experiment with dynamic computer engineering models to determine the basic power requirements for smart microgrid rural electrification [8]. One such study describes a smart microgrid computer simulation to determine the basic power requirements for electrification of a proposed hybrid off grid pilot site for 34 rural homes in Southern Africa [5]. Such studies raise awareness of the value of disaggregating the demand load data in model-based energy scenario design studies in support of more effective electrification planning and operations [9].

In hybrid renewable energy microgrids for off-grid community energy systems, least-cost operational energy management is a critical success factor in system acceptability [10]. This includes optimizing the technology selection and size of energy conversion components [11], as well as the adoption of an appropriate energy management system (EMS) with appropriate control automation strategies [12]. Microgrid EMS operational optimization is especially important because of the variability and fluctuations in supply generation from multiple renewable/fuel-based energy generation/storage systems, which relies on mathematically optimized energy flow control and load management on a strategic hierarchical control level [13][14]. In this context, disaggregated load data models are required for proper experimentation with computer modelled microgrid EMS control systems, especially since the EMS plays a crucial role in smartgrid acceptance for autonomous off-grid rural energy systems. Disaggregated demand load data further offers a means for analysing customer load device engagement scenarios aimed at increasing customer satisfaction, thus ultimately helping to improve the value proposition for smart microgrids in remote rural village energization.

Within this context, the IEEE Smart Village development concept calls for new thinking in terms of power generation, power distribution and demand side management that would help ensure sustainable renewable energy access to off-grid communities worldwide [15]. In a renewable energy rural smart village context, automated smart microgrid demand response research specifically requires discrete-time appliance disaggregated demand load data to experiment with control aspects around sustaining mission critical loads in rural energy systems [16]. Disaggregated demand load data is also required in the optimization of hybrid renewable energy systems for different technology system configurations in model based design approaches on energy planning software platform such as TRNSYS, HomerEnergy, EnergyPlan and EnergyPlus [17].

From a development perspective, demand load data and advanced metering infrastructure to measure and datalog disaggregated load data in small community microgrids are hardly available for isolated off-grid rural villages. Utilities, cooperatives and design engineers thus call for the development of discrete-time appliance disaggregated load simulation models able to translate discrete load management impacts into hour-by-hour changes in archetypal load shapes for traditional rural family villages. Novel rural village load simulation models should specifically have the ability to output time-series device disaggregated load data in terms of appliance use by time increment components for extended planning periods, including different seasons of the year. Such computer simulated disaggregated rural village datasets will be most valuable in engineering analysis applications where computational intelligence is used in cyber physical systems, for example transactive energy management in participatory smartgrid control for solar cogeneration systems designed for isolated rural villages [18].

This paper describes the development of a discrete-time and device load event disaggregated rural village electrical load profile simulation that uses load definition models to create logical time-series load profiles for rural villages. The smart microgrid load simulation model incorporates physical appliance energy ratings and device use behaviour patterns as basis for simulating disaggregated archetypal load profiles. The demand load profiles represent realistic and logical energy consumption patterns for typical small rural villages in formats suitable for import into various smart microgrid energy modelling and software simulation platforms.

2. RURAL ENERGY CONTEXT

IEEE Smart Village and ARE initiatives generally motivate design engineers to focus on the design and development of cost-effective small-scale renewable energy solutions that make effective use of community interaction in providing clean and sustainable energy services to rural communities [4][19]. They call on engineers to design new rural energy systems able to help to reduce poverty, based on the premise that the social value of small-scale energy systems can redefine community values [20]. In this study, we support the goals of the international initiatives and respond through research on smart microgrid intelligence systems able to support community demand response requirements (learned from community interaction). The focus of this section is to introduce the context of the traditional isolated rural African family village as a means of demonstrating the need to develop realistic load models for current off-grid rural village electrification and optimization research [21].

Most traditional rural African villages are located in parts of Africa where the land topography are mountainous terrains that over the years caused people to spread out and live in small homestead clusters or villages on the habitable parts of the hilltops and ridges. These villages are often located on ancestral tribal land or communal grounds in sparsely populated zones of remote municipal wards. The photo example in Figure 1 shows the typical rural electrification context for a small family village (kraal) in Africa, highlighting the technical engineering challenges of our present research. In these isolated homestead clusters, people typically stay in round indigenous huts (sometimes patterned) with thatched roofs in an energy context where the family live independently from municipal infrastructure.

Figure 1: Photo illustration of a traditional isolated rural African village homestead context seeking off-grid rural electrification solutions [22].

Inadequate rural grid infrastructure to villages such as in Figure 1 creates special challenges for local authorities obligated by government regulatory policies to provide *Free Basic Energy* (FBE) and *Free Basic Alternative Energy* (FBAE) services to poor households at lifeline tariff scales [26]. In this context, free basic electricity is pro-poor energy relief program terminology that describes the amount of electrical energy deemed to be sufficient to provide basic electricity services to a poor or disadvantaged household or family village. In general, FBE and FBAE are deemed to be sufficient to provide basic entertainment access and lighting in the case of non-grid connected supply systems (designers can add basic water heating kettle and limited ironing in cases where new grid electricity would be made available).

With small agricultural based homestead villages dotting the African landscape, many local authorities and traditional leaders are often challenged in their community and municipal development plans to provide freshly pumped water and energy services to these members of their constituencies [23]. Challenges with equitable Free Basic Services (FBS) to remote (rural) areas are generally referred to as the service backlogs (water, energy, electricity, sanitation, waste) in rural and municipal Integrated Development Plans (IDP) [25].

The South African Municipalities Sustainable Energy Transitions (SAMSET) project have made some efforts to support small scale embedded generation installers to help participating municipalities overcome these energy service provision challenges [24]. Contractors however found that, even if grid electricity may be available in remote rural areas, the choice between off-grid power generation through renewable energy systems (solar cogeneration, photovoltaic systems, biomass gasifier, etc.) or conventional grid extension for remote village electrification are often determined by a number of factors. These include the availability of grid infrastructure, the location economic distance limit, the operating hours of the renewable energy systems, the life cycle cost of the energy generation equipment, customer engagement issues as well as the micro-power system business strategy [27].

3. RURAL ENERGY LOAD PROFILE REQUIREMENT

Most clustered isolated rural kraal villages similar to Figure 1 are spread out over wide areas, making decentralized energy generation through solar renewable energy resources a viable technology solution. In this context, hybrid solar micro-combined heat and power (systems) are ideal for providing off-grid family villages with sustainable electrical energy and hot water. For rural villages with lower load demand (<25 kWh) located beyond the economic distance from an existing grid line, it has also been shown that hybrid solar and biomass gasification technology systems could be cost competitive solutions when compared to photovoltaic systems and grid extension (especially is sub-Saharan areas of Africa where agricultural and forest production residues are generated) [28].

Within this application context, Figure 2 highlights the central role of demand load profiles in the technical design planning and economic optimization of planned rural energy systems for remote rural villages. Load archetypes and load signatures are embedded in energy consumption patterns, and can be extracted if sufficient data is available in smart meter datasets in big data databases. With the appropriate search algorithms and load signature disaggregation frameworks, metered consumption data normally render valuable information on the nature of the load devices as well as their associated energy usage patterns [29]. In the case of non-electrified remote rural villages (Figure 1), very little meaningful statistical data (apart from general household surveys) is available on the potential daily/hourly energy usage and energy consumption patterns [24]. In most cases, remote rural communities have been living-off-the-land and have been using fuel-wood and other forms of fossil energy for decades. Without these households ever having the privilege or experiencing electricity access, it becomes very difficult to determine/predict post-electrification energy consumption patterns in the pre-electrification planning time period.

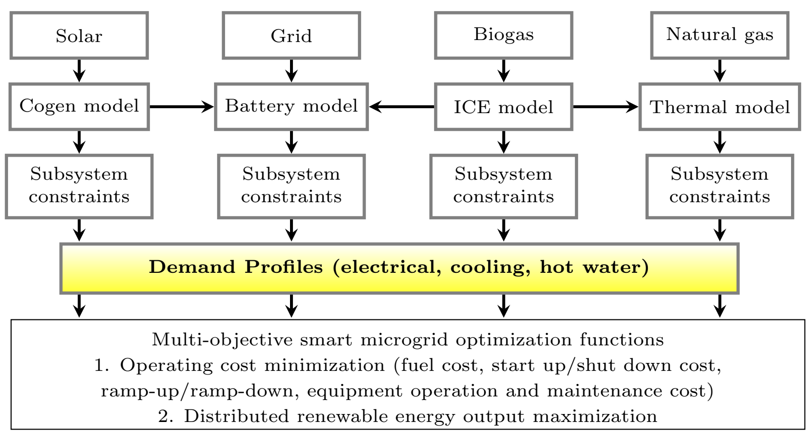

Figure 2: Flow chart of community microgrid optimization model highlighting the importance of reference energy demand profiles in rural microgrid electrification and economic operations optimization [30].

Since demand load data for isolated rural villages (in the context of Figure 1) are generally not available, the design optimization and energy management operation planning for new isolated rural energy systems will have to be performed through means other than with statistical load profile data analytics. In this respect we will have to rely on simulation techniques to analyse the behaviour of (low-voltage) smart microgrids using a customer behavioural based load profile generator [31]. For this purpose, Figure 3 shows a digitized software load profile definition window screen to emulate/synthesise (non-disaggregated) load profiles on a typical energy system modelling platform [32]. With this load definition formulation facility (for non-disaggregated loads), the Homer Energy analysis and simulation platform allows the design engineer to input an hourly time-series power consumption profile data in order to match renewable energy generation to the required load profile shape [33]. Important to note in Figure 3 is the discrete time format used to define the device disaggregated demand load data as discrete time series for a particular target day (in this case the household/village load profile is defined in terms of energy levels per hourly timeslots).

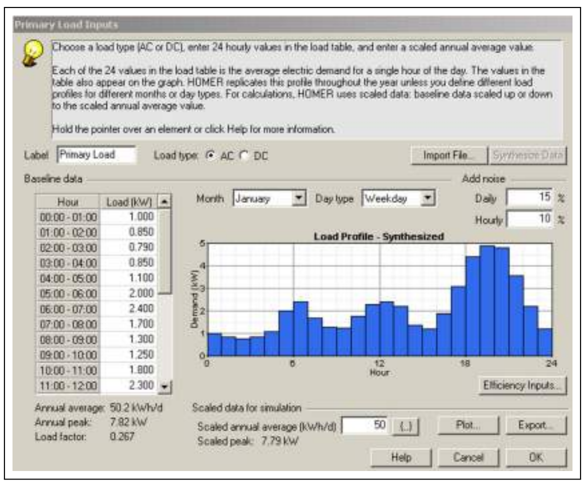

Figure 3: Example of non-disaggregated load profile definition screen for the Homer Energy load synthesis and operations simulation software platform [32].

From a load profile definition perspective, our interest is primarily in disaggregated load data. The aim with such data is to experiment with automated smart microgrid demand response, especially to study the ability to sustain mission critical loads in remote rural villages within the context of Figure 1. Demand response is an extremely important issue in off-grid and grid-connected solar renewable energy research, such that the Smart Electric Power Association (SEPA) and the Association for Demand Response and Smart Grid (ADS) have joined forces to tackle this challenge more effectively [34]. While most energy simulation platforms (such as Homer Energy) allow design engineers to define numeric consumption outputs by creating hourly power consumption profiles (as a means to match load demand to renewable energy generation), few load simulator platforms have the capability to define and generate *appliance disaggregated time-series demand load consumption data* for non-electrified traditional rural villages.

It was thus essential to develop simulation tools able to simulate realistic disaggregated load profile data for traditional rural villages. The simulation must export the demand load data in formats suitable for import into platforms such as Homer, TRNSYS, EnergyPlus, Matlab, Python, Opal-RT, NePlan, etc. Such demand load data will further enable us to predict how the obligated *free basic electricity* would be used in an isolated rural family village and how to optimize renewable energy systems to meet the predicted power demand on an hour-by-hour basis. These goals form part of our broader research goals, which is to assist local governments and municipalities to make the free basic electricity available to isolated off-grid rural village communities through shared community solar and autonomous smart microgrid energy distribution technologies [26].

Within this context, our main interest in this paper is thus on understanding rural village energy needs and to follow this up with the development of a rural demand load simulation focussed on determining simulated archetype load profiles for isolated rural villages. With such background knowledge and simulation model, relevant and realistic demand load profiles can be used in evaluating how energy technology would be able to match up or synchronize with timing of the daily and hourly demand patterns for an agricultural type homestead village (or kraal in a remote African region, where electricity have never been available before). Secondly, our research strategy include plans to implement multi-priority demand response and load curtailment in a smart microgrid environment. This means that our requirement is not only to generate simple amplitude based discrete time-series load profiles (shown in Figure 3), but to develop and extended load model that can generate appliance disaggregated time-series load profiles for traditional family size rural villages (Figure 1 context).

4. RURAL ENERGY NEEDS

In the context of understanding rural energy needs and rural village energy usage in load profiling, literature surveys around typical fuel types and fuelwood collection prove to be valuable in terms of understanding energy needs in the traditional rural energy context. To understand what future changes can be expected after electrification, one can compare the simulated demand load figures from a simulation model with daily energy consumption patterns from traditional fossil fuel collection and usage in rural areas in recently electrified rural villages [35].

The IEA estimates that the energy consumption per capita for rural households are typically between 50 to 100 kWh per year [2]. The report estimates that an annual consumption of 50 kWh per person for a five person household could be sufficient to, for example, operate two compact fluorescent light bulbs, a small battery charger and a cooling fan to run for about five hours per day. With the use of LED lighting and other energy efficient appliances, the electricity saved can be stored or applied elsewhere. The level of energy requirement may vary depending on income levels in rural areas, but it seems at least that there is consensus on the minimum amount of energy required [2].

For the Southern African Region, appliance ownership and usage of electrical appliances are taken from a study by Thom (2000). Table 1 lists the percentage of households that own certain appliances versus the percentages using these appliances frequently. This table is compiled from information published on the use of electricity by recently grid electrified rural households in South Africa [36]. It includes the ownership and usage of appliances such as a hotplate, a kettle, an ironing iron, and one or more refrigerators, radios, televisions and hi-fi systems.

Table 1: Appliance ownership for recently grid electrified households in rural Loskop, South Africa [36].

Service	% owning appliance	% using appliance
Lighting	100%	94%
Radio/hi-fi	84%	77%
Ironing	65%	61%
Television	52%	42%
Refrigeration	48%	48%
Water heating (kettle)	45%	32%
Cooking (hot plate)	45%	29%
Space heater	16%	3%

Table 1 further shows that low power lighting and entertainment electronics such a television, hi-fi systems and radios were amongst the most popular items owned and used with the introduction of electricity. Appliances such as kettles and fridges are further down the list, while high energy intensity appliances such as hot plate stoves and space heaters are of least importance and are least used even if they are present in the house. The study discovered discrepancies between electrical appliance ownership and electrical appliance use. This was noticed in the variation in frequency of use of household appliances. In comparing the column data in Table 1, it shows that in many cases the villagers do not use the appliances on a regular basis, even though they may own the appliance [36].

In terms of rural household energy consumption, it seems that the present perception in many newly grid-electrified rural areas is that electricity may be overly expensive for cooking, water heating and space heating (thermal energy needs) [39]. Appliance use patterns may thus be influenced by these same cost perceptions, especially in a context of newly electrified homes. These perceptions have likely been formed by pay-as-you-go type pre-paid meters that allow people in newly electrified homesteads to either monitor electricity token purchases or to visually monitor their electricity meters [39]. Such meters conveniently show direct electricity consumption and cost expenses in real time during usage on the distribution board in the house. This may be the reason why many users from a significant percentage of newly and existing electrified households in rural villages still continue to use more traditional fuels, such as biomass and paraffin for cooking, and candles for lighting [40][41].

Figure 4 shows the results of a 2013 study by the South African Department of Energy on the energy related behaviour and perceptions in South Africa. It was found that only one fifth of low income households are making use of electricity. For the rest, energy need were predominantly met through candles, firewood, paraffin and dry cell batteries [42]. To a large extent, this type of "fuel stacking" occurred in the medium income bracket, where 94% of households were using their access to electricity. The fuel stacking phenomenon is well documented and have been reported in many studies of rural and low income households [43][44]. The study also found that, for newly electrified low income households, electricity was mostly used to run appliances such as, lighting, radios, TV's and refrigerators. A very small amount of these households (7%) used electricity for cooking, while firewood (51%) and paraffin (38%) were other the dominant energy sources [42].

A survey conducted by Lloyd and Cowan (2004) in Khayelitsha (South Africa) provides important cues on the average levels of electricity consumption per month and per day. Their survey summary in Table 2 shows that the monthly energy consumption level for a rural household not cooking with electricity is around 150 kWh per month, while the energy consumption for electricity cooking households average around 210 kWh per household per month [44].

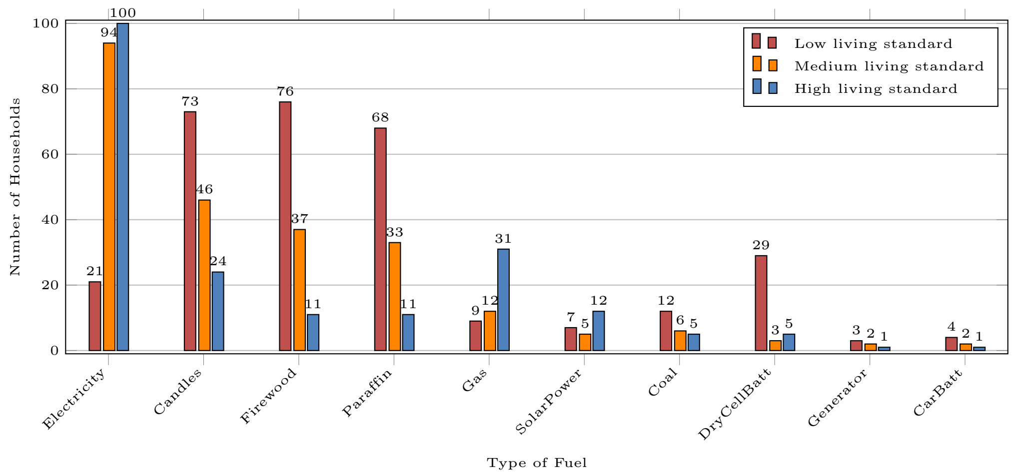

Figure 4: Rural African energy fuel source use by purpose and living standard levels [42].

Table 2: Monthly use of electricity and paraffin at homesteads in the Khayelitsha human settlement [44].

Homestead Type	**N**	**Paraffin Median**	**Electricity Median**
Households cooking with electricity	124	6 litres	210 kWh
Households not cooking with electricity	102	18 litres	150 kWh

Another interesting result from the study of Lloyd and Cowan (2004) is that many houses have access to electricity, but also used paraffin for cooking (fuel stacking). This confirm the findings of previous studies, showing that a significant percentage of newly electrified households continue to use alternative fuels [43]. In Khayelitsha, approximately 68% of households with a regular metered supply of electricity used electric stoves as main cooking appliance and the rest typically used paraffin stoves. Among non-electrified households, it was found that 92% of the households used paraffin stoves as main cooking appliance and the rest mainly used LPG gas.

A special observation should be made on battery operated devices, and they have need for charging of such batteries. Many battery-operated radios and modern day cellular mobile telephones require regular charging. This in itself has become an entrepreneurial opportunity for energy business micro-enterprises in rural areas [45][46]. Modern community energy solutions and local enterprise studies have shown an expected increase in the percentage of ownership of cellular telephones once electricity becomes available in their areas [47]. In one project in South Africa, the iShack project at the Sustainability Institute at Stellenbosch University, an entrepreneurial model was developed for incrementally upgrading informal settlements [43]. Such projects illustrated the potential for enterprise development as a result of rural electrification, an aspect that could potentially impact on the demand profile for a rural power system [48].

In terms of the sustainability of rural electrification, evidence from the above South African research on the effects of access to electricity in newly electrified houses have shown that the energy transition in rural households are largely driven by income levels [37]. Take note that most rural households are reported to be of low income status. The energy transition is also highlighted in the outcome of the Eastern Cape study through the proportional growth in electricity usage (relative to traditional fuel use) following a few years into the electrification process [38].

Drawing from experience gained in a rural African village energy profile scoping exercise, along with the information on potential energy usage discussed in this section, we are able to form an idea of the load profiles for rural and low income households. The next section combines this information with user behaviour patterns in a rural village to simulate realistic load profiles for targeted rural villages that may become eligible for future consideration in rural electrification plans.

5. VILLAGE LOAD SIMULATION

While shared solar power is an attractive energy resource to fuel village power and community microgrid systems, the challenge is that solar radiation patterns, weather patterns and the performance of solar energy conversion technologies vary from location-to-location. Model based design and desktop computer simulation models of particular solar renewable energy system configurations are therefore used to plan and scope village electrification projects around a particular design site and technology system. Since advanced metering infrastructure and load data are not always available to assist design engineers with the technical design planning and optimization of planned rural energy systems for remote rural villages, logical rural village load profiles have to be simulated.

In this section we describe the basic principles around discrete time disaggregated rural village electrical load profile simulations to support rural smart microgrid research. The simulation incorporates physical appliance energy levels and device use behaviour patterns as basis for simulating disaggregated archetypal load profiles that would represent realistic disaggregated energy consumption patterns for a typical isolated rural village. The proposed simulation outputs normal text and .csv format data, meaning the simulated load profiles can be imported directly into a range of software modelling and simulation platforms (ie TRNSYS, HOMER, EnergyPlan). In this way, the simulation data can be used to validate numerical simulation models for newly developed renewable energy systems. The output datasets further offer the opportunity to experiment with economic optimization and demand response in a multi-priority controllable load smart microgrid environment.

5.1. Village Load Simulation Approach

Prior research have been conducted on a statistical load profile prediction model for new residential consumers in South Africa as part of the development of a suite of electrical distribution pre-electrification software tools [8]. However, most of the isolated isolated rural African communities in our study focus (in the context of the illustration in Figure 1) have traditionally been dependent on subsistence farming in a pastoral lifestyle. From an energy profile perspective, most of these villages are still primarily involved in agricultural activities, meaning these villages will have its own unique set of energy profile patterns (village community behavioural patterns). Remote rural village load profile patterns could thus differ substantially from the statistically determined load profile patterns for urban and township electrification projects [8]. This makes it difficult to use statistically trained or Markov model trained smart village and smart home pre-electrification load planning tools [49]. The same goes for load profiles developed in collaboration with national grid utilities as decision support tools, these profiles being aimed at building energy load profiles prior to grid electrification for which metering data should be available [50].

Before the advent of big data and data analytics, the bottom-up approach to residential load modelling was developed by utility engineers to plan for urban microgrid developments. In this bottom-up approach, a model for domestic electric end-use was determined by establishing the load diagram of an area through a process of synthesis [51]. This modelling approach, started from knowledge around rural village socio-economic and demographic characteristics, unitary energy consumption and the load profiles of individual household appliances. Probability functions was also introduced in order to cover the close relationship existing between the demand of residential customers and the psychological and behavioural factors typical of the rural household. With these models, computer simulations of an electric load shape can also be determined as a time-series through electric load curve simulation or synthesis techniques [52]. This can be supplemented with a high-resolution domestic occupancy model able to make the energy demand simulations more realistic [53].

From a rural reference load profile perspective, we can define discrete time load profile levels for individual appliances based on simulations that operate on appliance power ratings and behavioural analysis/synthesis. In our research, simulating reference archetype energy profiles for a rural homestead or village is not only to define the average daily level or the energy consumption requirements for the rural settlement, but also to define realistic *disaggregated electrical load profile* reference patterns. Discrete digitized appliance and time disaggregated load data for rural villages is an extremely important requirement in our research since it is required to sustain mission critical loads using demand response and multi-priority load curtailment, mechanisms to compensate for the variability in renewable energy and solar resources in autonomous power systems.

The challenge is that few simulation platforms allow for the load profile to be determined in terms of *disaggregated data principles*. Within this context, the aim is to simulate realistic disaggregated digital electrical load profile reference patterns that could be used in demand response and critical load analysis for off-grid village community solar project research. The first sub-section describes the load simulation *Appliance Rating Inputs*, the *Behaviour Pattern Inputs*, followed by the *Village Load Simulation Model*. The experimental section of this paper shows the simulated discrete time disaggregated load profiles for a typical rural village.

5.2. Village Load Appliance Rating Inputs

Appliance rating parameters are required for the load simulation experiment. These parameters should include the *appliance configuration definitions* and the *appliance power rating specifications*. Exemplary appliance profile and rating parameters are specified in Table 3. It shows a list of an anticipated collection of appliances that may typically be used in a newly electrified rural family village. The table also lists the power rating for each appliance device. This input table represents the appliance definitions for any number and type of appliances that the design engineer can define and program into the simulation model configuration. In the example of Table 3, the village cluster includes a cluster of five households in the village, each equipped with outdoor security lighting (1 per house), indoor LED lighting (3 per house), radio receiver sets (1 per house), cellular mobile battery chargers (3 per house), television sets (1 per house) and shared refrigerators (2 per village) running as normal intermittent or user behavioural pattern loads.

Table 3: Electrical appliance definitions and average usage for a small newly electrified rural village.

	Rural village daily energy load			
Load Type	**#/Village**	**Individual load [W]**	**Hours/day**	**Load/day**
Indoor LED lighting	15	9	9	1215
Security lighting	5	9	12	540
Radio sets	5	4	16	320
Mobile/cell charger	15	4	5	300
Television	5	20	6	600
Refrigerator	2	40	10	1000
...	...	...	...	...
Daily Total				3.98 kWh

The load simulation model allows design engineers the option to define arbitrary combinations of appliances together with power consumption ratings for appliance in the targeted rural village design. The next sub-section describes how this average estimated daily energy consumption level can be disaggregated further in terms of discrete time events or (hourly) time-slots in which each appliance will draw energy from the village community microgrid on a daily basis.

5.3. Village Load simulation Behaviour Pattern

Another input parameter for the load simulation model is the appliance use behaviour. This parameter defines when and how much energy each appliance draws from the community microgrid as a digitized time-series. The simulation model uses the schedule defined in Table 4 to disaggregate energy usage into equipment or appliance loads for any rural village homestead into a certain discrete time events of any desired time resolution. The disaggregated time resolution in Table 4 is configured in time steps of discrete hourly events, but is should be understood that this resolution is variable and can be set between one hour down to five minute time steps.

In the example of Table 4, the estimated time of engagement for a number of appliances per household is shown in hourly time-slot increments. The indoor lights, for example, are

Table 4: Anticipated hourly electrical appliance usage patterns for a typical rural village appliance set.

Time	Indoor lights	Security lights	Radio sets	Mobile charger	TV	Fridge	…	House	Village
01:00		1					…	9.0	45.0
02:00		1				1	…	9.0	45.0
03:00		1					…	9.0	45.0
04:00	1	1					…	18.0	90.0
05:00	2	1	1			2	…	43.5	217.5
06:00	2	1	1	1			…	46.5	232.5
07:00	1	1	1		1	1	…	82.5	412.5
08:00			1		1		…	20.5	102.5
09:00			1			1	…	16.5	82.5
10:00			1				…	9.5	47.5
11:00			1			1	…	17.5	87.5
12:00			1	1			…	9.5	47.5
13:00			1			1	…	17.5	87.5
14:00			1				…	9.5	47.5
15:00			1			1	…	8.5	42.5
16:00			1	1			…	10.5	52.5
17:00			1			1	…	8.5	42.5
18:00	2		1			1	…	18.5	92.5
19:00	3		1	1	1	2	…	88.5	442.5
20:00	3	1	1	3	1	1	…	97.5	487.5
21:00	3	1		3	1	2	…	97.0	485.0
22:00	2	1		1	1	1	…	80.0	400.0
23:00		1				1	…	17.0	85.0
24:00		1					…	9.0	45.0
Total								0.239 (kWh_e)	1193.55 (kWh_e)

represented by the second column of Table 4. It shows that one of the indoor lights are switched on at 04:00, a second is switched on between 05:00 and 06:00, while three indoor lights are being used between the hours 19:00 to 21:00. This same appliance use schedule can be defined for the rest of the appliances, configuration information about the total daily expected electricity usage for each appliance (row: "Total"), each house (column: "House") and the amount used by a village (column: "Village").

This predefined rural household appliance load behaviour pattern input dataset is an important component in a bottom-up method of building an appliance disaggregated daily energy use profile in terms. It reflects major appliance activity and user behaviour spread throughout the day. The behaviour input parameters in Table 4 allow the designer to define spesific time interval periods during which arbitrary appliance devices my be drawing energy form the community microgrid. Keep in mind that the time resolution can be defined from 1 hour down to 5 minute time intervals. The load simulation translates these behaviour parameters into a discrete time-series that specify how much energy will be required or consumed by the load devices during each discrete time slot. It puts energy use in a time perspective for the designer and enables him to define correlations between household activities with physical energy use in a time-line of any reasonably desired resolution.

By using the proposed predefined household appliance usage and behaviour pattern time table data in a simulation technique, the appliance loads for each household can be artificially compiled from the potential energy time-of-use breakdown analysis in the behaviour pattern time table. The load simulation can thus define realistic hourly reference load profile for a rural homestead by using the user/appliance behaviour pattern in a load simulation described in the next sub-section.

5.4. Village Load Simulation Model

In the previous two sub-sections, it was shown how the appliance power rating and estimated time-of-use parameters can be used to define the daily energy requirements for a typical rural African village. The appliance rating parameters together with the appliance energy draw behavioural pattern parameters form the basis for simulating appliance disaggregated discrete time sequence load data or time-series load profiles. In this sub-section, the appliance definition inputs, appliance rating inputs and the behavioural pattern inputs are used in a numerical load profile simulation to define realistic disaggregated load profiles for formats suitable for rural village power planning processes.

The functional elements and building blocks that constitute the simulation model is shown in the block diagram of Figure 5. The *Demand Load simulation* block receives appliance power rating and estimated time-of-use parameter inputs from the design engineer definition inputs. From these inputs, the demand simulation model is able to generate discrete time appliance disaggregated demand load data for the predefined households in formats suitable for use in energy simulation and planning software.

The rural village load profile simulation model of Fig. 5 use the appliance power ratings in Table 3 together with the appliance and user behaviour in Table 4 to map the hour-by-hour contributions of the appliances onto the rural village load shape. In this way, an appliance (dis)aggregated load profile for a rural village can be defined by way of synthetically engaging individual appliances over a 24 hour period for one or more households in the village. It thus organizes the time-stamped disaggregated load samples into day-ahead tagged time-steps and

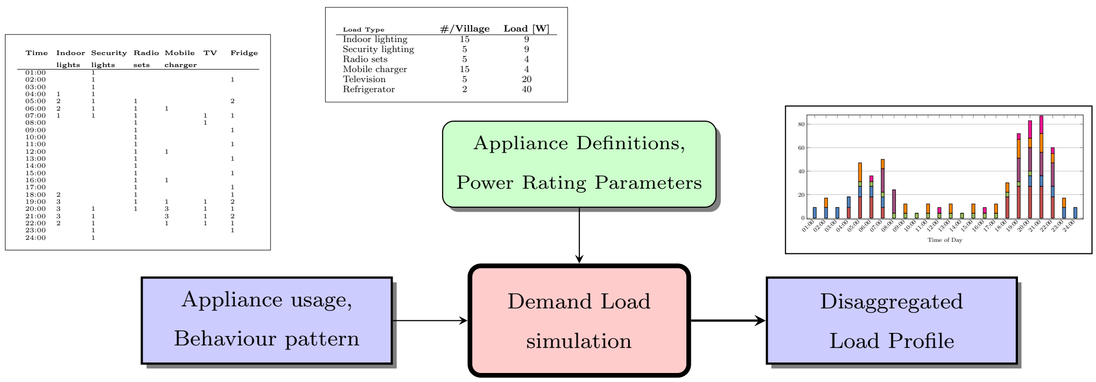

Figure 5: Flow diagram and parameter inputs towards disaggregated rural village load simulations.

load priority groups or layers. This synthesis principle is accrued for all of the appliances in the configuration definition list. In this way, the load simulation define realistic (dis)aggregated hourly reference load profile for a rural homestead by using the synthetic cumulation strategy based on the calculation defined in Equation 1:

$$p_e(t) = \sum_{i=1}^{N} a_i(t) \times r_i \times \delta t \tag{1}$$

where:

$p_e(t) =$ total electrical power use at time t [Watt]
$a_i(t) =$ number of i^{th} appliances on at time t
$r_i =$ i^{th} appliance electrical power rating (individual load) [Watt]
$N =$ number of appliances in the household configuration definition
$\delta t =$ simulation time resolution $[0.1 \cdots 1$ hours]
$t =$ time of day [i.e. $1 \cdots 24$ hours]

The computer simulation model thus simulate or "predict" the microgrid archetype load shape based upon the principles of disaggregation of the load shape. It disaggregated the load shape into different appliance components and user behavioural patterns. The hourly time-series load simulation method thus determines the geometric load profile shape by way of synthetically engaging appliances in hourly time-slots over a 24 hour time sequence.

Variations in the village size can be modelled as an energy magnitude variation. This means scaling the load profile energy magnitude based upon the average daily load for a village cluster consisting of one or more homesteads. A *scaling factor* is incorporated in the simulation to allow the design engineer the freedom to change the magnitude of the rural village load profile dataset by a factor of any real value. This scaling factor can also be used in a load size sensitivity analysis, for example to change the power units from Watt to kilo-Watt. Where the village size changes in a small rural microgrid, the magnitude of the energy consumption pattern may be scaled or adjusted in relation to the number of households connected to a rural microgrid. A scale factor disregards the potential distribution losses, a fair assumption given that the houses in a rural family village is typically in close approximation to the each other and the power generator.

5.5. Village Load Variability Modulator

User behaviour and presence changes may further affect the daily, monthly and annual peak load. This can be modelled as random variability in device disaggregated load profile and appliance usage. The solution is to incorporate a load pattern modulator into the load profile simulation block, as shown in Figure 6. In this way the load simulation offers the option to add random white-noise, heat degree-day or climatic weather data variability to the usage behaviour patterns for the individual appliances, in order to make the disaggregated demand load data more realistic. The load pattern modulation can also incorporate an occupancy modulation mode that would enable the simulation to modulate presence features onto the daily load profile patterns in order to create a demand load database for one or more full years.

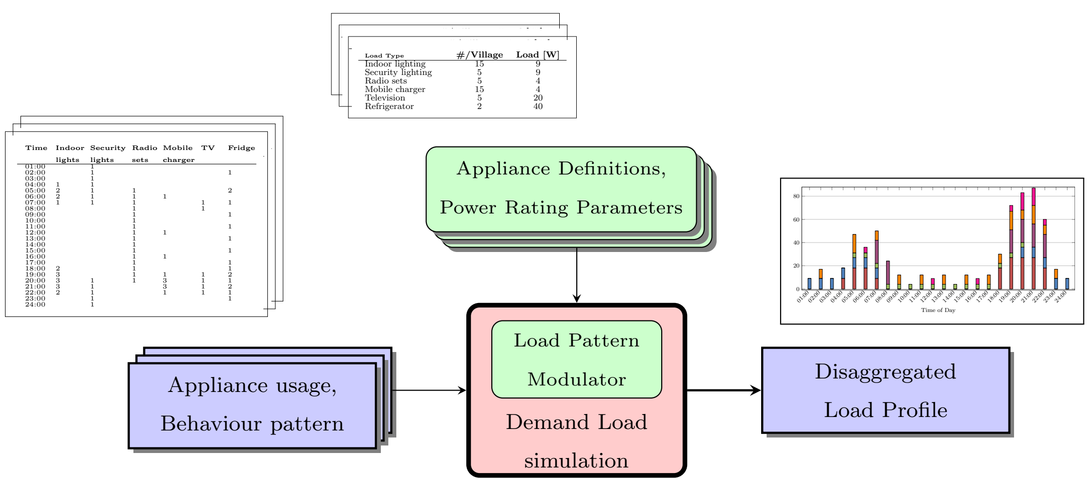

Figure 6: Rural village load simulation with variable appliance and behaviour pattern modulator to make village disaggregated load profile more realistic.

Fig. 6 shows the extended block diagram for demand load simulation model. The diagram includes options for appliance type variations amongst village homes, for which the model incorporates household differentiated appliance definitions. This feature enable the design engineer to define different appliance sets for one or more individual homesteads in the village. Secondly, the model shows the proposed load pattern modulator to add random variability (i.e. gausian distributed noise, temperature variability, etc.) to help make the disaggregated load profiles more realistic. The load pattern modulator in the block diagram modulator further incorporates a domestic occupancy mode to make the annual load simulation dataset more realistic [53]. In this mode, the demand load simulation concept is able to model the long-term presence behaviour of the occupants (based upon occupancy variations), thus creating an even more realistic predicted disaggregated load repository with synthetic load data curves for every day of the year.

Most energy simulation software platforms (Homer, TRNSYS, Simulink, EnergyPlan and Energy Plus) can also read plain text or .csv format load data from an import window. The rural village load profile simulation of Fig. 5 export the demand load datasets to a plain text or .csv format time series data file. The output file contain columns of numbers, one line for every simulation time step, with header lines and time stamps for each line. This means that rural village load profile benchmark models or benchmark load profiles can be created for any design day or for any extended period of time. Such benchmark time-series load models can be simulated according to the principles described above and uploaded onto software simulation platforms through system dataset import menus.

6. SIMULATION RESULTS

The NREL approach to rural electrification is an integrated, multidisciplinary and multi-functional approach that include applications development, options analysis and analytical modelling as part of pilot project development and program implementation [54]. This dynamic engineering computer modelling approach requires demand side load profiles to study rural energy options analyses. The details for such implementations are generally described by documentary guidelines compiled by the US National Renewable Energy Laboratory (NREL) village power program (ViPOR) [55]. The challenge of determining new load profiles for planned small family size rural village electrification projects can be overcome by simulating reference electrical and thermal load profiles for experimental research projects.

Anticipated load profiles for isolated rural communities, as potential customers to rural electrification, remains a critical resource in the design process. This data is required for the optimization of renewable energy systems in different technology system configurations. In terms of the NREL model, anticipated rural village load profiles are needed in modelling design approaches, where it enables a designer to plan around the village energy needs. This section therefore demonstrates the use of a dynamic demand load simulation model to define disaggregated load profiles for isolated remote rural villages.

6.1. Rural Village Load: Summer Season

In this experiment we use the rural village appliance set and appliance power ratings defined in Table 3 as basis for determining a typical disaggregated summertime load pattern for a rural village through load simulation. These input parameters represent the estimated time of engagement for each appliance per household in hourly time-slot increments. The simulation use this input data to compute the load profile for all of the appliances according to the method described earlier in this paper.

The simulation results for the characteristic appliance/user behaviour in summertime is graphically presented in the time-series interval energy data representation of Figure 7. In this demand load graph, the colour bars in each of the individual discrete time (hourly) segments represent the appliance load activity for that particular time-slot. The simulated disaggregated load profile offers a logical and realistic reference archetype energy profile for a rural homestead that can be scaled to represent one or more homes in the rural village. The disaggregated energy-use profile representation in Figure 7 essentially provides important information on how energy is used in the village. It thus shows how the reference daily electricity device loads defined in Table 3 is spread out over a full day 24 hour period in an accordance with the proposed hourly rural load emulation definition.

Since the digitized load profile emulation in Figure 7 shows the amount of electricity used in each time slot per appliance type, it can be observed that indoor lighting, cellphone charging and television usage is mainly limited to the mornings and evenings when inhabitants are at home. The simulated load profile results for the case study in Figure 7 further shows that the load simulation defines peak loads in the morning from around 05:00 to 07:00 and again in the evening

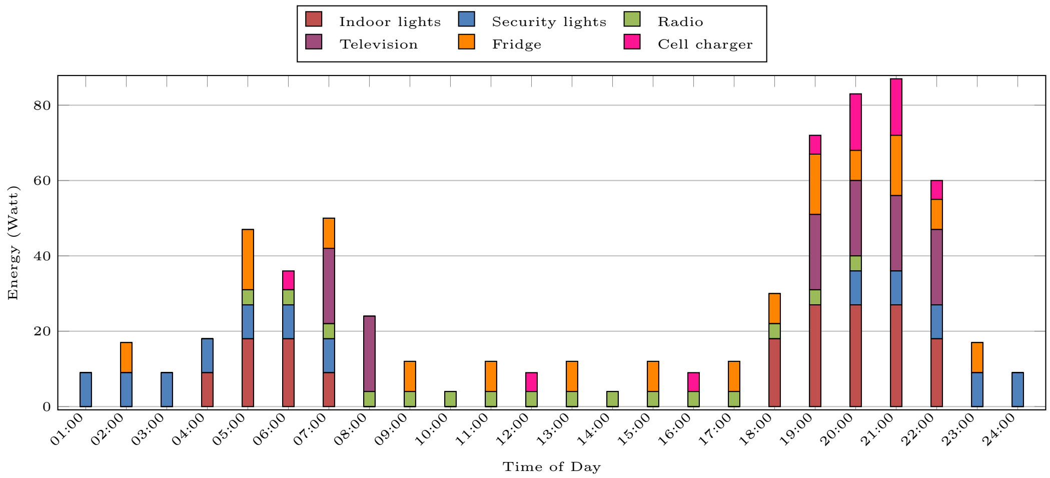

Figure 7: Summertime rural energy load profile archetype for computer modelling experimentation.

around 19:00 to 22:00, with very small amount of electricity used during the sunlight hours of the day. This simulated load profile with its characteristic early morning and evening peaks highlights the importance of energy storage to ensure reliable power day and night in community solar projects (through load shifting, battery backup and solar storage) [56]. It also highlights the importance of load profile characterisation in renewable energy efficiency management, since most energy in the rural village is consumed outside of peak sunlight power generation hours (around noon).

The simulated time-series demand load graph in Figure 7 offers a summertime scaled computer modelling dataset version for the determined hourly load profile in text or .csv excel format suitable for import into computer software simulation platforms such as TRNSYS, HomerEnergy, EnergyPlus, EnergyPlan, Python Developer, Matlab Simulink, etc. The simulated energy load patterns is also in a format suitable for use in optimal energy management schemes, which typically require such load profiles in the constraint and objective functions of multi-objective optimization for rural microgrid systems [30].

6.2. Rural Village Load: Winter Season

Seasonal variations in the daily load profiles is an important consideration in rural electrification since it will ultimately effect the energy generation and distribution control strategy. Thus, the load profile model should make provision for realistic loads for all seasons and for any number of rural households connected to the microgrid. For this reason, the simulation study is also interested in characterising changes in the shape of the daily load profile during seasonal variations. It means that we need to derive realistic load profile shape variations in terms of broad seasonal or monthly variations.

To accommodate seasonal variations, it is possible to once-again use the load simulation to synthesise or determine the anticipated rural village load variations in terms of load shape changes. We can thus follow the same procedure as we did in the previous section to define the simulation input parameters for the wintertime by selecting realistic times of engagement for the various appliances.

The seasonal effects of winter, such as temperature drops with shorter daylight time, can be better observed in Figure 8. Comparing the summer and winter emulation results, we see that apart from more electricity being used in the winter there is also some difference in the timing of the load profile peaks. The winter load profile starts its rise earlier and has a very wide evening peak, compared to the summer loads peaks which are sharper and more abrupt.

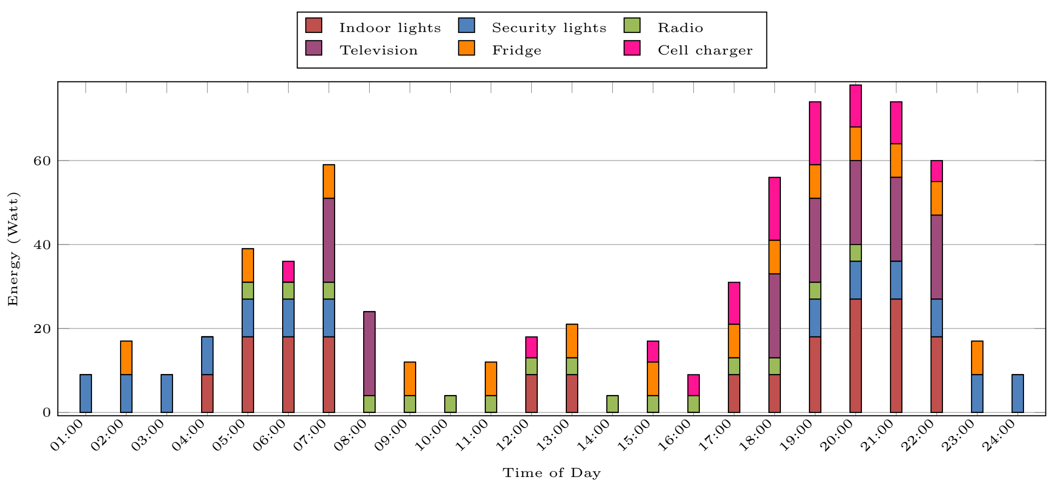

Figure 8: Wintertime rural energy load profile archetype reference for computer modelling experimentation.

The simulated discrete time-series graph in Figure 8 once-again offers a scaled computer modelling dataset version for the determined winter season hourly load profile in a format suitable for use in computer software simulation platforms (ie on TRNSYS, HomerEnergy, EnergyPlus, EnergyPlan, Python Developer, Matlab Simulink, etc.).

6.3. *Rural Village: Inter-Seasonal Transitions*

The discrete load simulation creates a full year of load data by using the summertime and wintertime daily load curves as anchor profiles and interpolating the inter-seasonal daily load profiles in-between. Figure 9 shows a comprehensive 3D plot of the interpolated seasonal changes of the load profile in the transition from summertime to wintertime. This illustration is based on a southern hemisphere time scale and shows the monthly averages for the hourly load profiles stacked behind each other for a period of one year (disaggregated load components not shown in the 3D plot as it would complicate the view). This 3D graph makes it possible to compare the average daily and inter-seasonal loads and allows us to compare the seasonal load profile characteristics (i.e. peak load times, peak load magnitude variations, etc.). The simulated disaggregated daily archetypal load profile models for a rural village from summertime through to wintertime in Figure 9 can be used to validate and compare mathematical and computer simulation models for storage and control automation solutions in rural energy and community micogrid systems.

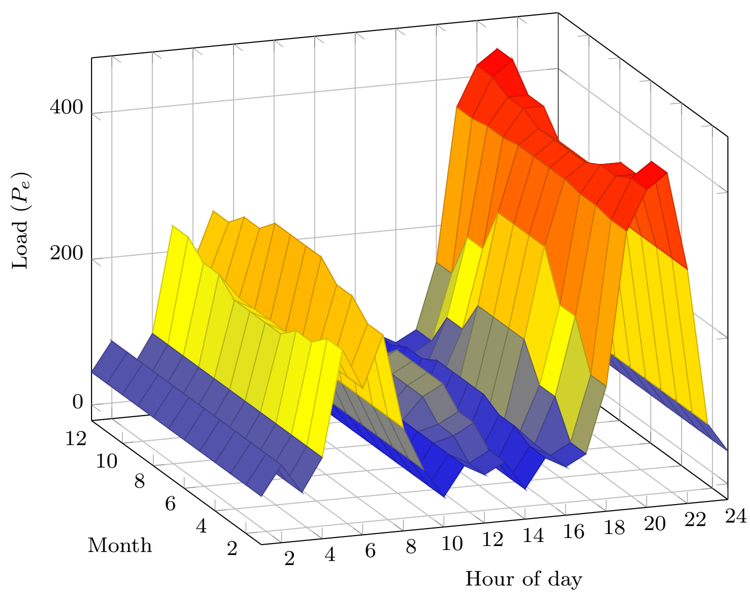

Figure 9: Reference rural village hourly electricity profiles for 12 months of year, Southern Hemisphere.

The demand load pattern simulation model is used to simulate the anticipated load profiles for any proposed rural village energy usage data in a disaggregated manner as illustrated in Figure 9. Predicted annual demand load profiles, used jointly with yearly forecasted weather pattern data [57], are valuable parameters in the validation and multi-objective optimization of rural smart microgrid systems [30]. This simulation can thus help design engineers to define appliance collection and incorporate any arbitrary energy use habits in order for the simulation to convert these habits into daily energy usage or appliance loads for each homestead or rural village.

Finally, in is important to know how the daily-average of the simulated load profiles compare with the anticipated load figures estimated in terms of fossil fuel consumption. From the user definable household appliance and appliance rating configurations, the estimated daily electricity usage per homestead or village can also be computed by the simulation. In the present case study example, the simulation estimates that the total daily electricity consumption for the sample five household village would be around 3.98 kWh per day. This equates to a renewable energy supply requirement of around 1452.7 kWh_e per year. The combined estimated daily village electrical load of 3.98 kWh represents the total estimated daily power load for a single isolated hypothetical newly electrified off-grid rural village. Say this defined rural village of five households include seven people per house, then the average daily load should equate to around 0.796 kWh per household or around 0.113 kWh_e per person per day (24 hours). These rural village load figures correlate well with the rural household and village power requirement estimates of the IEA and other sources discussed in Section 3 of this paper [2].

7. CONCLUSION

Appliance and time disaggregated load data is a mandatory important requirement for rural village electrification research since load data is the anchor to system optimization and operational efficiency assurance in current alternative energy systems. It is required in smart microgrid research aimed at sustaining mission critical loads and energy security, for example using demand response and multi-priority load curtailment as mechanisms to compensate for the variability in renewable energy and solar resources in smart microgrids. In this modern age of 21st century energy informatics, it still proves difficult to find digitised disaggregated time-series energy profile shapes for a a small typical indigenous rural village. This means that logical village load profiles have to be determined in a statistical or logical manner through computer simulations. Within this context, the aim of this paper is to describe a logical demand load simulation model that is able to define realistic disaggregated electrical load profile reference patterns for planned off-grid community solar project research projects.

The computer aided load simulation model was developed to help validate and compare mathematical and computer simulation models for smart microgrid storage and control automation solutions for energy system simulation models on computer simulation platforms. The discrete load simulations described and determined in this paper is valuable for future smart microgrid demand response research, especially where developmental researchers require archetypical type information about the geometry and disaggregated load characteristics of a rural homestead village energy consumption profile. These isolated rural village load profiles offer a basis for studying control automation and demand response in multi-priority controllable loads in a community microgrid environment. The simulated load representations will further be used in rural electrification planning and simulation experiments where software modelling platforms (ie TRNSYS, HOMER, EnergyPlan, Matlab, Simulink, Python, Opal-RT, NePlan, etc.) are used to scope and validate computer models for renewable energy and smart microgrid systems aimed at specific remote rural target sites.

CONFLICT OF INTEREST

The authors have no conflicts of interest to be declared.

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