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# A Bottom-Up Weather-Sensitive Residential Demand Model for Developing Countries. A Case Study of Abuja, Nigeria.

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ABSTRACT

The frequency of power outages being experienced in Sub-Saharan Africa mean that traditional methods of electricity demand forecasting which rely on directly observed demand data are inadequate for use in projections. Nevertheless, accurate forecasting methods are urgently required to ensure efficient power system operations and expansion planning. To address this gap, we develop a novel method to estimate unsuppressed electricity demand for developing countries. This follows a bottom-up approach based on socioeconomic data and a time-use database developed from a householder survey, which are used to generate household profiles using a Markov Chain approach. These profiles are then converted into electrical load time series by a series of appliance models, using reanalysis weather data to accurately represent ambient conditions for the generation of cooling demand profiles. We apply our method to a Nigerian case study, obtaining the first time series of unsuppressed residential electricity demand for the country using the first Time-of-Use Survey (TUS) for Nigerian households. We validate our model outputs using the results of a small-scale residential metering trial, which yielded a correlation coefficient of 0.97, RMSE of 0.04, and percentage error of 6% between measured and model data. This evidences that our method is a credible and practical tool for electrical demand studies in developing countries. Using the model, the forecasted domestic demand for Abuja Electricity Distribution Company ranges between 345 and 575 MW, while that of Nigeria ranges between 3,829 and 6,605 MW

*Keywords*: load modelling, load management, power demand, stochastic processes, cooling, buildings.

## 1. Introduction

Historical underinvestment due to inadequate funding and inefficient power sector operations, along with a rapidly growing population in developing countries, particularly in sub-Saharan Africa, have resulted in a significant population of about 620 million people without access to grid electricity [1]. The total installed generation capacity largely exceeds available production capacity in many of these countries, due to constraints in power generation, transmission and distribution, resulting in inadequate energy supply to their electrified population [2].

To manage the limited energy supply, network operators resort to load shedding to manage inadequate energy allocations from the grid. This load shedding, which can either be pre-planned or arbitrary, occurs at different transmission voltage levels of the network by connecting and disconnecting customers. While the frequency and duration of outages vary

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across countries (2–2500hours/year), customers increasingly resort to the use of costly back-up diesel generators [1].

At the transmission level, the inability of generation to meet demand results in an essentially flat measured load duration curve that does not reflect the actual spatial and temporal variations in demand. To plan investment effectively and efficiently in large scale generation, network infrastructure and potential renewable energy necessary to provide appropriate supplies it is important that realistic estimates of the *unsuppressed* demand are used. Techniques currently employed in forecasting demand including time series [3], econometric [4], and computational intelligence [5], cannot readily be applied, as studies in developing countries have established an absence of causality between demand and economic variables [6], an incoherent trend in historical demand due to load shedding [7], and typically neglect portions of historical data due to influence of suppressed demand and system losses [8]. The application of weather variables in forecasting demand in Sub-Saharan Africa is also of limited value. Two forecasts from southern Africa [9] and [10], have both stated that industrial demand, the major driver of demand is independent of temperature, and hence do not include temperature in their national forecasts. Unavailable temperature data has also been the reason for non-inclusion in forecasts [11]. In northern Africa, a study has shown that a 1% increase in average temperature will increase electricity consumption by 1.32% [12].

Typically, demand forecasting tools such as IAEA's Model for Analysis for Energy Demand (MAED) [13] are employed in Sub-Saharan Africa, but these are limited due to the unavailability of data required for sectoral energy projections, with generated load curves impacted by data gaps due to frequent power outages.

Alternative approaches include the 2009 demand study by the now defunct Power Holding Company of Nigeria (PHCN), which employed a sigmoid growth curve method to forecast peak demand, using per capita residential energy consumption, electrification rate and load factor assumptions [14]. These estimates were obtained from the residential energy sales by distribution companies, and as a result still reflect *suppressed* demand, low electrification rates and no consideration of weather sensitivity.

Energy surveys and measurement campaigns are also employed to estimate demand trends. A United Nations Development Programme (UNDP) residential metering study data [15] used month-long metering of around 35 households in 6 Nigerian States in 2012/13 to estimate domestic consumption. However, the reliability of annual estimates is limited as they are extrapolated from monthly measurements subject to supply interruption, partial capture of appliance-use and omission of household socioeconomic data.

For renewable energy supply assessment, it is important that analysis does not simply report peak demand, as increasingly, the variation in demand and its relationship to production becomes more important [16]. To this end, a method is required to estimate time series demand that is unconstrained by suppressed demand data. In addition, the substantial differences in climatic conditions across geographically larger countries with warm temperatures indicates potential significant space cooling demand, which means that spatial characteristics are also important.

Meeting these requirements lends itself to a bottom-up modelling approach able to capture essential features of energy use given broadly similar electrical appliance ownership and requirements in the residential sector. The heterogeneous nature of energy use, electrical equipment, and sectoral behavior in the commercial and industrial sectors would require an intensive modelling exercise currently beyond the scope of this study.

While bottom-up modelling of residential energy demand is no longer exclusively in Western nations such as the UK [17] and Sweden [18], it is still mainly applied in Western nations. The climate assumptions in these models differ significantly from the tropical climate and socioeconomic conditions e.g. appliance ownership, that apply to residential electricity demand in Sub-Saharan countries. As such, simple translation of existing models would not be credible.

In this paper, we therefore develop, demonstrate, and validate a novel bottom-up weather-sensitive residential demand model which is suitable for use in developing countries. In doing so, we aim to make three contributions to the existing literature. First, we develop a novel method to model unsuppressed electricity demand in developing countries. This provides a means of estimating demand even when directly observed data is unreliable because of recurrent outages due to grid collapses or load shedding, and facilitates use of time series operation and planning approaches that are standard in Western nations either directly or through providing means to cross-validate simpler methods and examine the credibility of limited measurement data. Second, in our case study, we apply this model to the Nigerian power system, obtaining the first weather-sensitive time series model of domestic energy demand in Nigeria driven by household activity and weather patterns. Third, the Time-Use Survey (TUS) which is used as input data for this model is itself of interest, being the first of its kind for Nigerian households.

The remainder of this paper is arranged in the following way: Section 2 provides a description of the model, section 3 discusses the case study, section 4 gives a presentation of the results which are discussed in section 5, and finally, the conclusions are made in section 6.

## 2. Methods

An overview of our modelling approach is shown in Figure 1. At the core is a residential demand model which provides a time series simulation of energy use from appliances and air conditioning (A/C) for an individual household. Household profiles are stochastically generated from information on occupancy, appliance ownership and household activity derived from a TUS. The household profile data is then converted to electricity demand using appliance and A/C models.

Weather data is used to simulate the ambient conditions which influence A/C and lighting use. Since data gathering is the most expensive part of most modelling efforts, our model is capable of simulating demand from the individual household level up to many thousands of households with defined socioeconomic characteristics, providing robust aggregations at regional, Distribution Company (DISCO), and national levels. This ensures that a single input dataset can be used for a wide range of operational and planning purposes. Regional and national aggregation is achieved using the after diversity maximum demand (ADMD) method, which is widely used by network operators in aggregating residential demand, such as in the UK [19] and Australia [20].

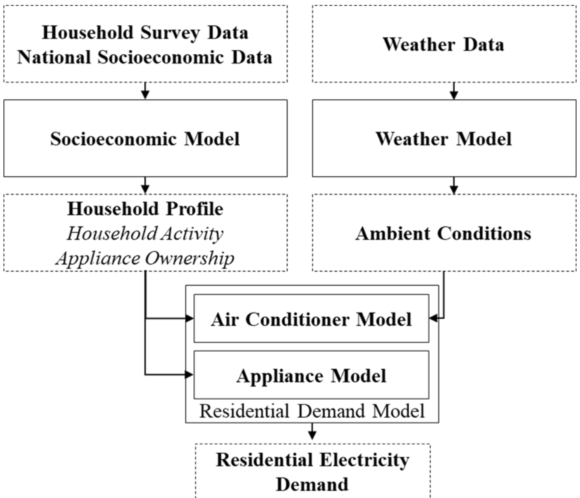


**Fig. 1**. Overview of the modelling approach

### *2.1 Household Time-Use Survey*

The development of model household profiles requires a TUS. This is a detailed survey of household activities, which can be used in building household activity profiles, as performed in previous UK studies to represent 22 [21] and 10,000 [22] households, respectively. TUS survey results are available for some countries, including in Sub-Saharan countries with energy supply shortages, *e.g.* industrial use in Cameroon [23] and residential use in Botswana [24]. For our Nigerian case study, a survey has, to our knowledge, not been conducted [25]. It was therefore necessary to design and conducted a bespoke survey to obtain information on activities and household energy usage.

TUS surveys address areas of concern with the use of metered data from households that experience frequent load shedding, such as the failure to capture demand served by back-up generators, and also the tendency for household demand to shift to periods of restored power supply which tends to inflate demand during periods of power supply uncertainty. Using activity diaries and questionnaires which ask participants to detail their activities assuming uninterrupted supply reduces this risk, as activities are better distributed throughout the day and not impacted by load shedding.

Our Nigerian questionnaire requested the preferred times of performing basic household activities; a half-hourly resolution was used to make this manageable for participants. It focused on typical weekdays and weekends only, again to reduce complexity for respondents. It also gathered data on appliance ownership, building types, occupancy and customer demand classed. More details about the survey can be found in Section 3 below.

The information captured was sufficient to capture realistic activity patterns and household profiles. While household activity times as recorded by respondents may differ in practice, across a larger number of respondents there is no reason to assume a systematic bias, since a concentration of activities was anticipated to occur around similar times.

### *2.2 Household Profiles*

A key feature of residential demand modelling is the simulation of household occupant behavior. Occupant activity is the key driver of electrical energy consumption, as it determines usage of appliances. In our model, daily occupancy profiles of each household are constructed based on results of the TUS' half-hourly activity diary and are simulated using a combined probabilistic and Markov Chain approach. In simulating household activity, transitions are implemented between 'active' and 'inactive' states. Active states are defined as periods when the household engages in activities that require electricity, while inactive states are periods the household does not engage in such activities, e.g., sleeping times, during which only cooling demand is present.

The survey information is used to develop a probabilistic model of household activity. From a TUS diary, a Markov Chain transitional probability matrix is created by summing all transitions between active *x* and inactive *y* states [26]:

$$p_{xy}(t) = \frac{\sum_{y=1}^{Y} n_{xy}}{n_x(t)} \tag{1}$$

where $p_{xy}(t)$ is the transition probability from state *x* to *y* between time intervals, $t$ and $t+1$, $n_{xy}$ is the number of transitions between the states *x* and *y*, and $n_x(t)$ is the population in state *x* at time *t*. This is applied to the household survey diary to generate the transitional probability matrix as shown in Fig 2. and the probability of initial conditions across all the households. The probability distribution of the household initial condition is determined by the activity state at $t(1)$. In simulating activity in the model, transition occurs at each time step $t$ by comparing the probability $p_{xy}$ to a generated random number, to determine the household active state.

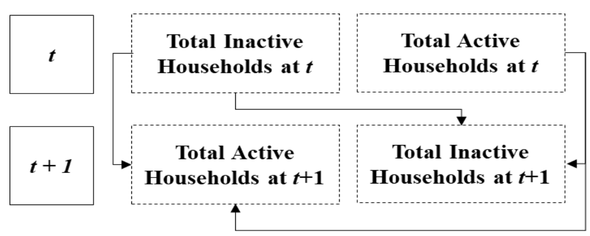


**Fig. 2**. Transition Probability Framework

Household electrical demand is driven by household activities including sleeping, cooking, etc. The activity in any one household is simulated based on the activities of the 'population' who possess similar socioeconomic and appliance characteristics. From the survey, a time distribution for each household activity is generated by calculating the probability of activity occurrence among all active households in the survey population in each time step. Activity probabilities are then obtained using:

$$p_{j,wd}(t) = \frac{\sum_{wd=1}^{2} n_{j,wd}}{n_{wd,active}(t)} \tag{2}$$

where $p_{j,wd}(t)$ is the probability of occurrence of activity type $j$ on the day type (i.e. weekday or weekend) $wd$ at time $t$, $n_{j,wd}$ is the total number of households performing that activity; and $n_{wd,active}$ is the total number of households that are active. An example of the cooking activity probability distribution is shown in Fig. 3 and described in detail in the next section.

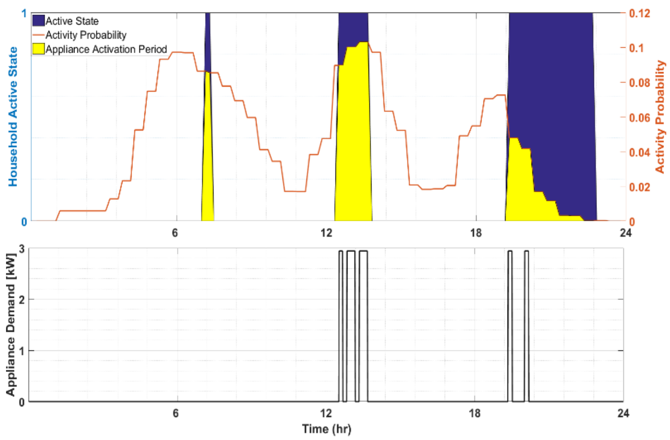


**Fig. 3.** Example of the conversion of household active states to cooking appliance (electric cooker) demand

### *2.3 Appliance Demand Model*

We model 24 separate appliances. Some, such as TV sets, electric irons, and electric fans, are standard across all households while others, such as A/C, microwave ovens and washing machines, are only present in more affluent households. The household active state is converted to electrical energy demand using the power ratings of appliances, activity profiles, an appliance scaling factor, and the duration of appliance use. For a household that owns an appliance, the demand of that appliance is determined by its current active state at time *t*, the activity probability linked to that appliance at *t*, the appliance demand (or stand-by) and the duration of appliance use.

To represent the arbitrary nature of human use, appliance activation occurs if a generated uniform random number is less than the product of the appliance activation probability and the appliance-scaling factor during the period of likely appliance use. This can be expressed as:

$$p_{j,a}(t) = p_j(t) \times hh_{state}(t) \tag{3}$$

$$D_a(t) = \begin{cases} R, & rn \leq p_{j,a}(t) \times s_{j,E} \\ 0, & rn \geq p_{j,a}(t) \times s_{j,E} \end{cases} \tag{4}$$

where $p_{j,a}$ is the activation probability of appliance *a* associated with activity *j*, $p_j$ is the activity probability and $hh_{state}$ is the household active state. $D_a$ is the appliance active power demand (W), *R* is the appliance rating (W), $s_{j,E}$ is the appliance scaling factor, and *rn* is a random number generated with uniform distribution. The scaling factor is a measure of the probability of the daily activation of an appliance based on its annual use.

Fig. 3 shows the conversion of a household active state to an electric cooker power demand for cooking events. The cooker rating is 3kW is selected from a uniform 2.5-4.0 kW range from typically available cookers [27]. The red line shows the overall probability of activity in the household, the three blue regions show actual household activity in a day and the yellow regions show the appliance activation period when the electric cooker could be activated. To simulate cooking, the random number test then determines appliance activation, and as is shown for this simulated household, cooking occurs at lunchtime and in the evening. For each cooking activity, the duration is selected from a uniform 15-45 min range, obtained from existing TUS data from across Africa [28].

The duration of appliance usage is determined from the survey results for 'human activated' appliances and duty cycle studies for other appliances [29]. Lighting demand has been modelled using an implementation of the algorithm developed by [30], and hourly solar irradiance data.

### *2.4 Air Conditioner Demand Model*

A/C usage is implemented using a zonal (room-by-room) approach for modelled buildings. The household active state and occupants determine the activation of the A/C in each room, with the cooling demand calculated as described in [31]. In an air-conditioned room, the heat balance is the sum of the heat loss (cooling) from the A/C and heat gains from infiltration, occupants, appliances, conduction and fenestration [32]. The change in air temperature due to the heat balance can be expressed as:

$$C_{air}\frac{dT_{room}}{dt} = q_{gains} - q_{ac} \tag{5}$$

where $C_{air}$ is the thermal mass of air (J/K), $T_{room}$ is the room temperature (K), $q_{ac}$ is the cool air outflow from the A/C and $q_{gains}$ are the heat gains within the room (W).

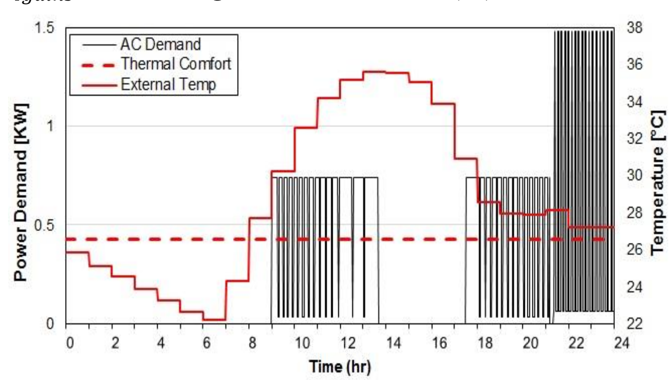


**Fig. 4**. An example of household cooling demand

The heat gain across each building fabric component in the room is modelled separately and combined to calculate the room heat gain. For the walls, both internal and external walls (active surfaces) are modelled. For single room apartments and flats, they are modelled as externally located in the buildings, e.g., apartment blocks. The heat flow across the building fabric can be expressed using [32]:

$$q_t = k((T_{EM} - T_{room}) + (T_{S,t} - T_{EM})f) \quad (6)$$

where $q_t$ is the heat gain (W) at time *t*, $T_{S,t}$ is the sol-air temperature (*K*), $T_{EM}$ is the mean sol-air temperature over 24 hours and *k* (W/K) is the product of thermal transmittance (W/m$^2$K) of the building fabric and its area (m$^2$). *f* is the decrement factor that accounts for the time lag effect of heat flow across the building fabric due to the thermal inertia of the material [33]. The sol-air temperature models the effective external building fabric temperature accounting for the incident radiation $E_t$ (W/m$^2$) on the vertical surfaces:

$$T_{S,t} = T_{E,t} + \frac{\alpha E_t}{h_O} \quad (7)$$

where $T_{E,t}$ is the external air temperature (K) and $h_O$ is the heat transfer coefficient for radiation and convection at the outer surface (W/m$^2$).

The cooling model operates during two time periods, the night-time sleep period, and the day-time active period. For night-time cycles, the A/C is activated at sleep times and operates till the wake-up time. For the daytime cycle, the A/C is activated when the household is active and for the duration of that active period and switched off otherwise. To account for the operation of the A/C unit (5) can be rewritten as:

$$C_{air}\frac{dT_i}{dt} = q_{gains} - wq_{ac} \quad (8)$$

where *w* is the thermostat status (either on or off). Thermostat operation is governed by [34]:

$$w = \begin{cases} 0, & T_{room} \leq T_s - \Delta \\ 1, & T_{room} \geq T_s + \Delta \end{cases} \quad (9)$$

where $T_s$ is the set-point temperature (K) chosen by the household for comfort, and Δ is the dead-band. The A/C is switched on when room temperature exceeds the upper bounds and switched off below the lower bound.

The resulting A/C demand is given by:

$$D_{ac} = wq_{ac}/EER \quad (10)$$

where $EER$ is the energy efficiency ratio (9.47Btu/h.W). An A/C system is rated at 2.6kW with a 6m$^3$/min airflow rate [31]. Natural infiltration is modelled as 0.5 room air changes per hour [33].

Fig. 4 shows an example of A/C operation in a 2-bedroom flat. It operates from 9am-1.30pm and from 5.30pm-12.00am when the household is active, and the maximum comfort level is exceeded. It is off during the inactive afternoon period and when the temperature is below the maximum comfort level in the morning when the household occupants are asleep. Cooling demand between 9.00pm-12am represents the aggregate cooling demand from each A/C unit in the 2 bedrooms.

### *2.5 Household Demand*

The total household active power demand $D_{hh}$ is the sum of demand *D* from all household appliances *A* including the A/C:

$$D_{hh}(t) = \sum_{a=1}^{A} D_a(t) \quad (11)$$

### *2.6 Aggregation Model*

To aggregate the demand profiles generated from the simulated households, we develop a bottom-up model that allows for flexibility in the aggregation grouping criteria, including socioeconomic and spatial information, using the after diversity maximum demand (ADMD) method.

The ADMD method is typically applied in low voltage networks to forecast demand, and estimation is a challenging exercise due to differences in customer characteristics. In practice, the ADMD value tends toward the average demand of a diverse customer group. The use of the residential model enables study of the ADMD within the same customer consumption category and limits the averaging effect on peak demand.

The ADMD value is calculated from the time series residential demand model output. The model is run multiple times for a customer demand class and the ADMD values are then used to estimate the peak demand using the customer population for each State. The ADMD value is given by:

$$ADMD = \lim_{J \to \infty} \frac{1}{J} \sum_{j=1}^{J} MD_j\,(t) \quad (12)$$

where $MD_j$ (MW) is the demand of customer *j* of a group of customers *J*, at the period of maximum simultaneous demand.

A single distribution company (DISCO) typically supplies several administrative areas, consisting of customers in different tariff classes. To perform regional aggregation, the peak demand *PD* (MW) for each DISCO can be expressed as:

$$PD(t) = \sum_{g=1}^{G}\sum_{n=1}^{N} RC_{g,n}\, ADMD_{g,n}(t) \quad (13)$$

where *g* is each administrative area in the DISCO region (*G* is all areas served by each DISCO), *ADMD* is the after diversity maximum demand value (W) for each customer class *n* (*N* customer classes), and *RC* is the number of customers in each customer class. The demand values for each DISCO are then combined to determine national values.

## 3. Case Study

The purpose of this case study is to demonstrate and validate the use of our residential electricity demand model. We apply our model to generate regional and national aggregate demand estimates for Nigeria with emphasis on peak demand; estimates which, to date, are not publicly available. In Nigeria, 11 distribution companies with locational monopolies serve 6.4 million customers (Fig. 5), with 84% of those residential [35]. In Nigeria, the customer class or tariff class as defined by the electricity regulator based on its definition of peak demand for each class. It categorizes residential customers according to their energy use: R1 customers use the least energy (<100W), R2 customers consist of single and 3-phase customers typically in apartments and whole buildings (< 12kW), R3 represents maximum demand customers (< 400kW) typical of small estates and government houses, and R4 customers represent the largest demand class (<16MW).

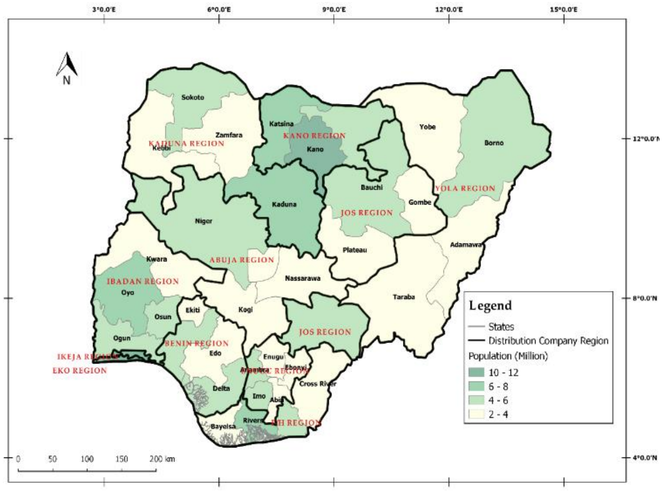


**Fig. 5**. Nigeria Population Distribution

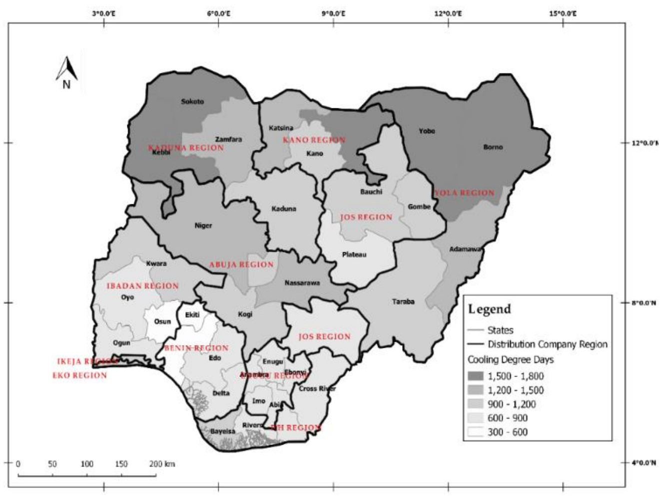


**Fig**. **6**. Cooling Degree Days - Nigeria

Published national socioeconomic data on building stock, appliance ownership, and customer population are used to create household profiles in each tariff class at State level which is then aggregated.

In estimating demand, the uncertainty in peak demand must be accounted for. This uncertainty is treated by applying a scenario-based approach to the socioeconomic data; specifically, we use three appliance ownership scenarios for the entire country. We use 2015 weather conditions for each State in the residential demand model, using reanalysis weather data, such that the time series reflects variability in ambient conditions between the various states (Fig. 6).

### *3.1 Socioeconomic Data*

#### *3.1.1 Household Survey*

Two questionnaires were used: one administered through face-to-face interviews, and one conducted online. Both were carried out between March and May 2016 in the nation's capital, Abuja, which was selected for this study due to its population diversity and fair representation of people originating from all over the country. The questionnaires were distributed through the Abuja Electricity Distribution Company (AEDC).

The sampling methodology recommended by [36] was used to determine the sample size. An assumed 5% error margin and 99% confidence interval level required a target sample size of 750 for the face-to-face survey. With an adjusted confidence interval level of 95%, and the same error margin, a sample size of 350 respondents was targeted for the online survey.

532 respondents fully completed the face-to-face survey (71% response rate) and 305 completed the online survey (88% response rate). Table 1 provides a breakdown of the face-to-face respondents. While income-related questions were not included in the survey due to their invasive nature, urban (54%) and rural (46%) residential customers are both well represented, limiting the risk of wealth bias. The tariff class representation is also reflective of the national domestic customer distribution [35]. The average household occupancy was 4.35, similar to official national estimates of 4.5 [37]. Results from the household survey is available in [38].

**Table 1**
Description of Household Survey Respondents

| Variables | Classification | Number (%) | Data from [34,36] (%) |
|---|---|---|---|
| Settlement Type | Rural | 243 (46) | 65 |
| | Urban | 289 (54) | 35 |
| Tariff class | R1 | 42 (8) | 2.9 |
| | R2 | 445 (84) | 97 |
| | R3 & R4 | 10 (2) | 0.1 |
| | Unmetered | 35 (7) | N/A |

#### *3.1.2 Building Characteristics*

The model assigns a building type to each profile, with probabilities based on the national distribution of building stock type: single room apartments (68%), flats (6%), duplex (1%) and whole buildings (25%) [37]. Single room apartments, typical of high-density residential areas in Nigeria, usually have just one window and one door. Other building types representative of medium and low-density residential areas are allocated bedrooms using data from [39], and have been designed using [40]. For walls, sandcrete blocks have been selected for the model; these are extensively used in the building industry in Nigeria. They are hollowed blocks, with one-third of a typical block volume, and a density of 1,947kg/m$^3$ [41]. The window area is are modelled as 24% of the area of the external walls. Single-glazed windows, typical of Nigerian homes, and usually fitted with mosquito nets, have been assigned an internal shading factor of 0.8. Additionally, an orientation relative to due south is assigned to each building; this affects levels and timing of sol-air temperatures, but the effect is relatively small (~2% difference between best- and worst-case building orientation).

#### *3.1.3 Appliance Ownership*

Appliance ownership data for selected appliances from the survey is presented by customer tariff class in Table 2. R1 customers, typically rural and low-income customers, have the lowest appliance ownership rates for all appliances, especially for high rated power appliances. R2 customers, typically urban customers, have higher appliance ownership rates than R1 customers. R3 customers, which are typically high income and residential estate customers, have the highest appliance ownership rates.

Ownership of high-power rated appliances are high compared to the national figures for Nigeria as show in Table 3. The low national ownership rates from the published statistics for Nigeria are impacted by the electrification rate of (51.3%) in the country [37]. The National Bureau of Statistics (NBS) survey includes unelectrified respondents which reflects in the low appliance ownership figures, as the quality of electricity supply is expected to influence electrical appliance purchases. With a higher electrification rate in Nigeria's urban areas, the appliance ownership is higher than that of the national average. The disparity in ownership rates could also be attributed to the survey location, Abuja (FCT), having higher population wealth indicators compared to the national average [42].

**Table 2**
Survey electrical appliance ownership by tariff class (%)

| Appliance | R1 | R2 | R3 & R4 |
|---|---|---|---|
| Fan | 88 | 96 | 100 |
| Refrigerator | 38 | 70 | 100 |
| Freezer | 5 | 41 | 70 |
| Microwave Oven | 5 | 35 | 100 |
| Kettle | 21 | 43 | 70 |
| Shower | 0 | 14 | 40 |
| Electric Cooker | 17 | 27 | 100 |
| Television | 86 | 93 | 100 |
| Electric Iron | 69 | 88 | 80 |

**Table 3**
High power rated appliance ownership comparison (%)

| Appliance | Survey | Nigeria (All) | Nigeria (Urban) |
|---|---|---|---|
| Washing machine | 23 | 1.5 | 3 |
| Electric cooker | 26 | 3.4 | 5.8 |
| Electric shower | 31 | N/A | N/A |
| Microwave oven | 35 | 3 | 6 |
| Air conditioner | 39 | 2.6 | 5.1 |

**Table 4**
Appliance ownership scenarios

| Tariff Class | Low | Medium | High |
|---|---|---|---|
| R1 | Rural | States | Urban |
| R2 | States | Urban | Survey |
| R3 & R4 | Survey | Survey | Survey |

The appliance ownership data from the survey undertaken in Abuja cannot be applied to all States in Nigeria due to differences in household income across the country, therefore the 2015 national appliance ownership data and survey results [42] were both used in the model. However, the national data on appliance ownership is presented at regional, rural, and urban levels and cannot be directly used since it represents appliance ownership across all tariff classes within a region. There are six regions comprising of at least five States, while rural and urban data are representative of the entire country.

In order to map appliance ownership to electricity customers within each State, account for uncertainty in assumptions, and also represent the demand impact of economic development, manifesting itself through appliance ownership, three scenarios have been developed for each tariff class, as shown in Table 4. The 'Rural' level represents nationally low rates of appliance ownership in rural areas. The 'Urban' level represents nationally high rates of appliance ownership in urban areas. The 'State' level gives the rates of appliance ownership in individual States which lie between rural and urban levels.

The scenarios show progressively greater appliance use within classes. For (typically rural) R1 customers the 'Rural' level is used for the low scenario, increasing to 'Urban' levels in the high scenario. For R2 customers, we consider a range from 'State' to 'Survey' levels. High ('Survey') rates are used in all scenarios for R3 and R4 customers with incremental adjustments made to the AC ownership in the Medium and High scenarios.

The appliances used in the model are based on their prevalence at the national level. Household profiles within the same tariff class are generated for each simulation. The list of appliances for each scenario can be obtained from [38].

### *3.1.4 Thermal Comfort Level*

Outdoor temperatures are the main determinant of A/C usage, and the relationship between indoor and outdoor temperature defines household comfort thresholds [43]. A thermal comfort study for Nigeria revealed an indoor temperature range of between 23.5 and 26.6°C [44]; households are sampled from a uniform distribution within this range.

### *3.1.5 Customer Population*

The residential customer population data for each DISCO has been obtained from [35] and used for the weighted summation in Eq. 13 to derive the peak demand.

## 3.2 Weather Data

The lighting and A/C models use ambient weather data. The sol-air temperature requires temperature and radiation time series. These are derived from NASA's MERRA-2 dataset [45] which is available on an approximately 50×50 km longitude-latitude grid. Hourly 2-metre air temperature data has been used directly for $T_{E,t}$ while total irradiance $E_t$ is calculated from the surface incoming shortwave flux and extra-terrestrial radiant flux. The radiation variables are used to calculate diffuse and direct radiation which varies with surface orientation (and have been applied to hourly solar PV modelling [46]. The Boland-Ridley-Lauret method [47], has been adopted for diffuse fraction estimation given its predictive strengths over comparable models and ease of application [48]. Well-established trigonometric relationships [31] with latitude and longitude are straightforward to apply to the hourly temperature and irradiance data to simulate the external temperature of the building.

## 4. Results

### *4.1 Residential Demand Model Validation*

Using the above models and data, we simulate energy consumption at tariff class level. Aggregate demand data for each tariff class was generated by simulating 1,000 household profiles, as no significant change was observed in the model output data for larger simulation sets. A full year simulation of demand in Abuja FCT was performed for each tariff class with the survey appliance ownership data to assess model performance.

Appliance ownership is the source of energy consumption disparity among tariff classes as shown in Fig 6. An individual R3 customer tariff class represents the demand of a small estate of about 200 units, hence the results presented here indicate a typical household within that estate. The demand profile presented is the simulated demand profile of a customer within that estate. All three profiles have morning and evening peaks, representative of typical residential demand profiles, however, the peaks are only prominent in the demand profiles for the R2 and R3 classes who typically own more electrical appliances and demand more energy than R1 customers.

From Fig 7, the daily aggregate mean (± std. dev.) energy use reveals R3 customers have the highest energy use 19.6 (±3.3) kWh, R2 customers use 10.8 (±1.6) kWh and R1 customers use 2.1 (±0.2) kWh. Floor area contributes to this as R2 and R3 customers typically occupy larger buildings requiring more cooling.

The annual aggregate mean (± std. dev.) energy use by building type shows that, unsurprisingly, whole buildings have the highest consumption at 4.8 (±0.7) MWh, duplexes use 4.0 (±0.6) MWh, flats use 3.6 (±0.6) MWh and single-room apartments use 3.1 (±0.5) MWh. The impact of the socioeconomic assumptions chosen for each scenario can be observed on the average daily peak demand per tariff class shown in Fig 8. The R1 customers average daily peak demand range between 0.23 - 0.74kW, R2 customer results range between 0.55 – 1.10kW, while the R3 customer results range between 1.21 – 2.24kW.

To validate these results, we use the UNDP measured profiles for Abuja FCT obtained between March and April 2012 [15], with modelled demand for Abuja FCT using MERRA-2 weather data for the same period. The load profiles from the UNDP study represent only the hours with grid supply and does not include the periods of load shedding. Since the UNDP study omits details on the building types and tariff classes of measured households, comparisons are made with simulation results for R2 tariff customers for the 'high' scenario. This is reasonable as the UNDP study is limited to households with A/C and the R2 tariff class, with A/C ownership, and represents over 95% of residential demand [30]. Validation result data is presented in [38].

Aggregate demand profiles of the modelled and measured data are presented in Fig. 9, with modelled data presented as averages for individual months (February to April, the dry season) and overall. There is a good similarity with peaks

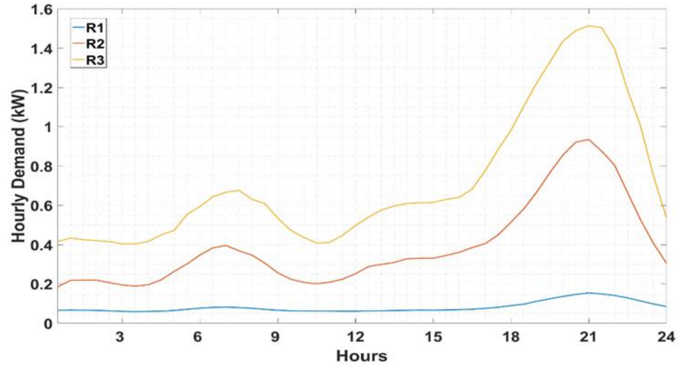


**Fig. 6**. Hourly demand profile by Tariff Class

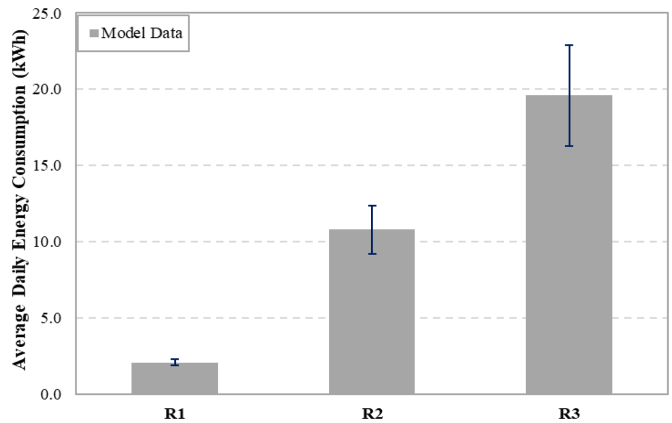


**Fig. 7**. Mean daily energy consumption by Tariff Class

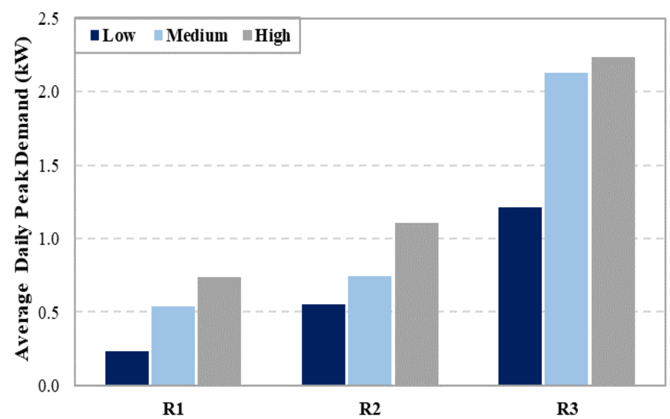


**Fig. 8**. Mean daily peak demand by Tariff Class and Scenario

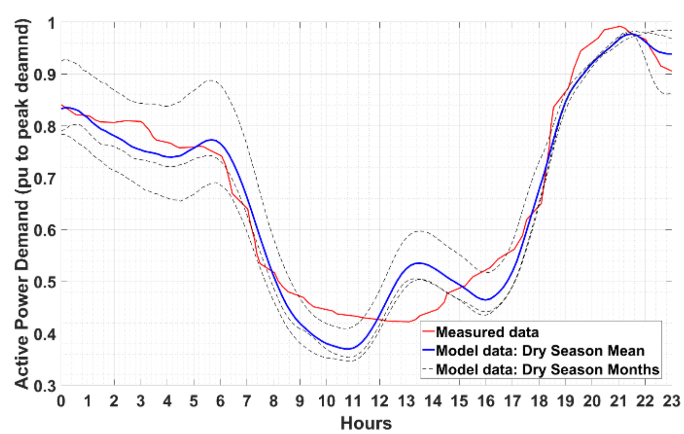


**Fig. 9**. Residential load profile: modelled vs measured data [15]

occurring in the same period, but modelled data shows an earlier pick up of afternoon load (12pm) which can be attributed to the concentration of activities resulting from the coarser time resolution of the TUS. Early morning temperatures increase from February to April and this is seen in the modelled early morning cooling load for those months, demonstrating the temperature sensitivity of the model. The statistical similarity with measured profiles (r = 0.97, RMSE = 0.04, bias = 6%) suggests the model is suitable for simulating aggregated load profiles for Nigerian households.

### *4.2 National Residential Demand*

Each of the 11 DISCOs serves one or more of the 37 States. Each State is modelled as 4 loads, one per tariff class. Modelling each State separately as presented in Fig 10 allows the spatial variations in weather to influence demand. An individual set of profiles is generated from the demand model for each tariff class for each State within the DISCO (total: 1000 profiles × 4 tariff classes × 37 States). Using the residential customer population of each State, the ADMD model generates hourly peak demand, which is then aggregated for each DISCO. Aggregation is performed for each appliance scenario.

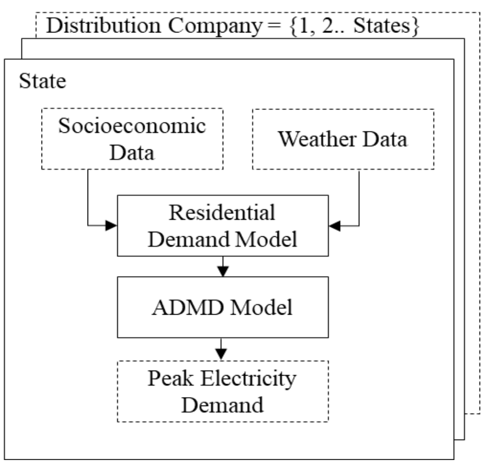


**Fig. 10**. Residential Demand Aggregation Framework

The results for the 4 States served by Abuja Electricity Distribution Company are shown in Table 5. While all States have R2 and R3 customers, wealthier and more urbanized States have more R4 and fewer R1 customers. All tariff classes are present in AEDC. 66% of residential customers served by AEDC live in single-room apartments, 10% live in flats, 23% live in whole buildings, and 1% in duplexes. The dominance of single room apartments limits appliance ownership and space cooling. The differences in appliance ownership results in a range of peak demand values. Given the current low appliance ownership in AEDC (e.g. 0.7% A/C ownership), as ownership levels reach national urban levels, significant increases in peak demand are observed. Between 'low' and 'high' scenarios there is an overall 67% increase in peak demand, with R1 demand increasingly more (307%) than R3/R4 (68%).

National residential peak demand estimates and time series data for 2015 are generated with the ADMD model. Table 6 shows the national aggregate peak demand estimate for the scenarios along with individual DISCO demand at this peak (note that not all DISCOs experience peak simultaneously). Across the scenarios, the demand estimates for DISCOs with the highest values are largely driven by a combination of high customer population (Ibadan) and high appliance ownership (Ikeja, Enugu and Benin). From the 'low' to 'high' scenarios, significant change is seen in Kano (185%), Kaduna (136%), Yola (132%) and Jos (128%), the DISCOs with the lowest estimates, due to the increase in appliance ownership in their States of coverage, which catch up to the national urban estimates. An increase in per capita energy consumption in these 4 DISCOs is also driven by an increase in cooling demand resulting from the effect of warmer temperatures in their States of coverage.

**Table 5**
AEDC Domestic Peak Demand Estimates (MW)

| Tariff Class | Low | Medium | High |
|---|---|---|---|
| R1 | 1.5 | 4.6 | 6.1 |
| R2 | 318 | 406 | 526 |
| R3 & R4 | 25 | 41 | 42 |
| Model Total | 345 | 451 | 575 |

**Table 6**
National Domestic Peak Demand by DISCO (MW).

| Distribution Company | Low | Medium | High |
|---|---|---|---|
| Abuja | 345 | 451 | 575 |
| Benin | 482 | 610 | 773 |
| Eko | 406 | 432 | 527 |
| Enugu | 483 | 544 | 826 |
| Ibadan | 622 | 777 | 1,205 |
| Ikeja | 531 | 576 | 703 |
| Jos | 199 | 351 | 452 |
| Kaduna | 156 | 233 | 368 |
| Kano | 116 | 216 | 329 |
| Port Harcourt | 415 | 483 | 669 |
| Yola | 77 | 110 | 178 |
| **National** | **3,829** | **4,783** | **6,605** |
| [14] | **3,732** | **4,183** | **4,917** |

The national peak demand estimates indicate a range of values between 3,829 and 6,605 MW. A 73% change between 'low' and 'high' in comparison to the individual DISCO demand growth rates reflects the diversity in affluence and climate-driven need for A/C. The differences between scenarios are also visible in the weekday hourly national residential demand time series, which are also compared to national weekday load curves which also includes non-residential demand [49] in Fig. 11. The profiles exhibit patterns typical of residential households with 2 diurnal peaks, unlike the national load curves (including non-residential demand) which for reasons previously mentioned, tend to be flat and are unrepresentative of hourly responses in demand. As they are based on the same underlying household behavior data across the different locations, the 3 profiles exhibit similar patterns. However, the socioeconomic variables drive differences in hourly magnitude. The monthly peak demand pattern shown in

Fig. 12 is reflective of the underlying cooling demand in each DISCO. Although less prominent in the low and medium scenarios, the effect of cooling demand increases over the dry season months (November – April) is observed in the high scenario.

A direct comparison with the PHCN study estimates for 2015 is not possible due to the scenarios having a completely different basis and socioeconomic assumptions. However, it is useful to compare the range of peak demand estimates from the bottom-up model with those from PHCN. These cover values between 3,732 and 4,917 MW, only 43% of the range covered by our bottom-up model.

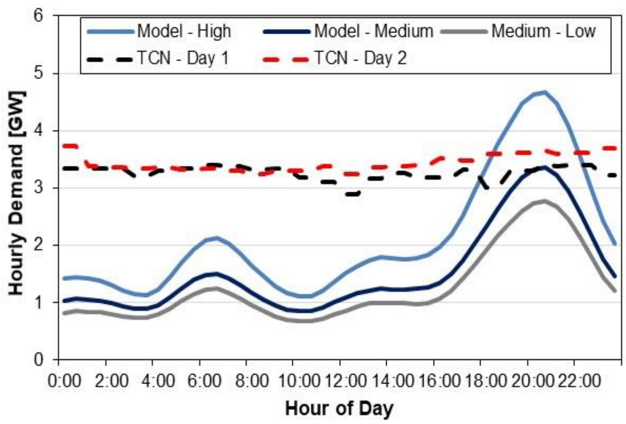


**Fig. 11**. Aggregate national residential demand time series

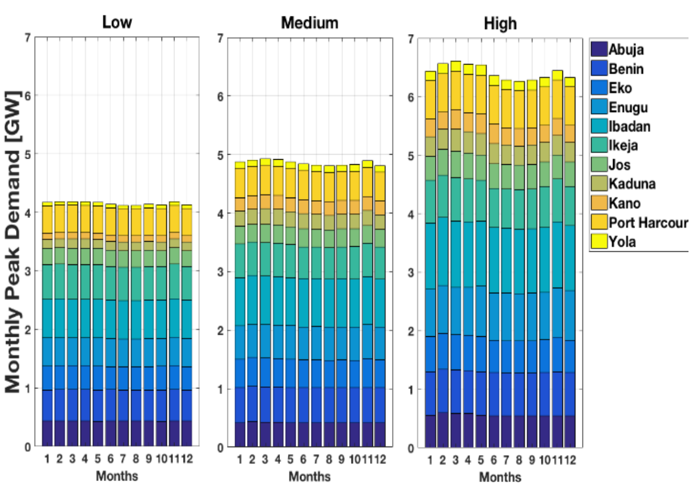


**Fig. 12**. Monthly Peak Demand Pattern

The PHCN study employed energy sales as the baseline (which inherently relates to suppressed load), constant per capita energy use and the same growth rates for all customers. As a result, there is less differentiation of energy use between customers. The demand in the modelled ‘low’ scenario is around 5% lower than PHCN’s lowest estimate partly because of the appliance statistics used for the low scenario included non-electrified customers. The ‘high’ scenario peak demand is 32% higher than the top of PHCN’s range. The much greater appliance ownership rates from the household survey translates to higher per capita consumption than in the PHCN study. This suggests PHCN significantly underestimated demand from higher rates of socioeconomic change. Previous demand forecast studies undertaken in Nigeria and limited by suppressed demand data, give 2015 demand forecasts ranging from 3.2GW [7] to 35GW [8]. The lower end of the range is closer to the forecast results from the current study and PHCN forecasts. Since it represents total demand, its domestic demand component will be significantly lower than the unsuppressed domestic demand forecasts discussed in this paper. Hence the use of suppressed demand data in forecasting causes an underestimation of the demand.

## 5. Discussion

In this paper, we have presented a weather-sensitive bottom-up stochastic demand estimation model which relies on socioeconomic information, survey results of household activity patterns in and reanalysis weather data, instead of measured demand data which is often problematic in developing countries. The model can simulate residential electrical demand at the level of individual households, regional, and national level. The explicit representation of appliance ownership by tariff class allows for projections of aggregate demand that assess the sensitivity of customer groups to the impact of electrical appliance ownership changes resulting from evolving socioeconomic conditions. The inclusion of weather sensitive demand, notably A/C (and lighting) is important given the diversity in climate across countries.

To demonstrate and validate the model, we have applied it to the Nigerian power system. In the absence of a national TUS database for Nigeria, a householder survey diary was employed to capture as best as possible household electricity consumption patterns under constant power supply conditions. This TUS is itself the first of its kind for Nigeria and provides a reasonably robust basis for an analysis of unsuppressed demand, which has not previously been possible at this level of detail.

Ultimately, the household diary is limited in its ability to accurately replicate all households in Nigeria, as it is restricted in volume, time resolution and location. For example, surveys for the UK cover 25,000 people across the country and have a 10-minute recording window, which would allow a more refined approach in modelling. However, if the survey day coincides with supply interruptions, as is almost inevitably in a developing country, it may not reflect true unsuppressed demand. Locational diversity would also help capture ‘local’ practices, which may be important given the cultural diversity in Nigeria.

There are other areas where development could valuable. The estimates are limited to customers that are currently connected to distribution networks, but this could be extended to capture non-electrified households. Although the TUS was designed explicitly to gain an understanding of unsuppressed demand, the dynamic nature of the model presents opportunities to extend the analysis to more realistic views of energy use under outage and recovery periods.

It also allows for analysis of the socioeconomic indicators on energy planning. The current tariff regulation in Nigeria stipulates a monthly demand of 50kWh for R1 customers. However, our model shows consumption of up to 63kWh, caused by higher appliance ownership in Abuja FCT. This is significant for energy tariffs because R1 customers are subsidized by other tariff groups meaning any breach of load allocation will cause commercial losses for DISCOs [35].

The Nigerian case study focused on peak demand, as this is a key indicator of generation and network capacity requirements. However, the model is a time series model and can be applied to a wide range of traditional and more recent network operational and planning applications including grid integration of renewables. Future demand estimates can be achieved by updating the model with revised national socioeconomic data and projected future weather conditions.

## 6. Conclusion

The frequency of load shedding currently being experienced in many developing countries means that traditional methods of demand forecasting are inadequate for projecting future use. The availability of load time series and curves that can be produced using the bottom-up model described in this paper are valuable to a wide range of stakeholders, from operational and long-term planners to policy makers. They can help optimize grid operations, facilitate power planning studies, including smart grid assessments in rural and urban electrification projects. If the socioeconomic model is to be extended to increase the current electrical appliance suite, along with adjustments to the appliance efficiencies, it could also be helpful for bottom-up energy efficiency studies.

Further developments are possible, and facilitated by the flexible nature of the model, but we have demonstrated the usefulness and relevance of our models, in the process obtaining data on Nigerian electricity demand, which will itself be useful to the Nigerian electricity sector.

## 7. Acknowledgments

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