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Experimental validation of an electrical and thermal energy demand model for rapid assessment of rural health centers in sub-Saharan Africa

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ABSTRACT

Rapid deployment of health service infrastructure is underway to meet the growing needs of populations in sub-Saharan Africa, however the energy infrastructure needed to support high quality services has tended to lag. Understanding the electrical and thermal energy needs of health centers constructed with local building methods and materials and operating outside of the jurisdiction of heating, ventilation and air conditioning (HVAC) codes is complicated by a lack of appropriately scaled and configured energy system design frameworks and validation data for dynamic simulations. In this work we address this gap by linking the thermal envelope performance of health center buildings under heating and cooling loads with measured indoor air temperature, meteorological conditions, and operational electricity demand. A résistance-capacitive type energy balance model is parameterized using typical health center architectural data for sub-Saharan Africa (floor plans from Uganda and Lesotho) and heat transfer characteristics; to achieve this energy flows between HVAC equipment, internal loads, and ambient conditions are simulated on an hourly time step with indoor temperature thresholds representative of thermostat settings. A typical meteorological year dataset for Lesotho is used as a case study, validated with indoor temperature measurements and power metering at four health center sites spanning a daily patient load ranging from 15 to 450 per day over rural and urban communities. High resolution electricity measurements from smart meters installed at the clinics are used to close the energy balance and form the basis of a probabilistic method for forecasting long term hourly electricity demand in African health centers. These data and the corresponding method have relevance to energy system design for health clinics across sub-Saharan Africa, especially those featuring intermittent renewable generation. The integration of these two modeling approaches constitutes a novel tool for sizing and costing energy infrastructure to meet operational demand at health centers in both urban and rural areas of developing countries.

Highlights: A gap in current understanding of rural health center energy demand is identified. A building energy model (BEM) is parameterized for rural African health centers. The BEM is coupled with electrical demand data and validated using a case study. A method for creating synthetic demand forecasts using measured data is proposed. Energy demand prediction via the above can enable health center energy system design.

Keywords: Africa, Health center, Energy, Building energy model, Dynamic simulation, Probabilistic load forecasting

Nomenclature	
a	Absorbance
A	Area
Ib	beam irradiance
k	thermal conductivity
Q	heat flow
τ	Time
U	overall heat transfer coefficient
V	Velocity

1. Introduction: Powering health infrastructure

In sub-Saharan Africa energy for health centers is increasingly prioritized by planners pursuing a general strategy of increased energy access for the approximately 600 million people who lack electricity services [1-3] This stems from the expectation that electrification contributes to positively impacting health outcomes through improved service delivery, i.e., use of modern equipment and procedures, electronic medical records (EMR), etc. Meanwhile market forces have contributed to lowering the cost of energy equipment, e.g., solar panels, therein expanding the budgetary ability to provide electricity at remote clinics. While new health centers being built in unelectrified areas may include such energy systems in the design, including updated architecture for energy efficiency, the far more extensive portfolio of existing facilities operating without power could also benefit from retrofitting and upgrading. The sizing, configuration, and costing of these retrofit energy systems depend critically on understanding the dynamics of energy demand in a representative setting, something which to date has simply been impossible due to a dearth of relevant data to underpin the evaluation of energy (electricity or heating cooling) demands at these facilities.

1.1. Health center demand dynamics

The energy demand, and time-dependence of demand, correlate with a number of factors such as size of the facility (footprint and patient load), building construction and thermal performance, types of equipment and services deployed, and the meteorological conditions driving heating ventilation and air-conditioning (HVAC) loads - as well as the extent to which the latter are sourced from electricity or (as is more common for heating applications) fuels such as LPG, coal, or biomass. A health clinic energy generation system design tool, such as those developed by [4,5] or the authors previously in [6,7], must therefore perform a simulation of energy system yield over time, matching generation capacity (as a function of resource, e.g., solar, availability) to a (calculated, inferred, assumed, or measured) demand dataset. To do so most accurately requires knowledge of diurnal, weekly, and seasonal variation in demand, data which are typically unavailable. The synthetic construction of a demand dataset is most often pursued using inventory based assessment methods, such as [8], that generally fail to capture actual observed usage patterns [6]. This work proposes an alternative, measurement-based approach to generation of the demand datasets required to drive the annual supply/ demand simulations necessary to optimize sizing of energy infrastructure.

1.2. Measurement-based demand forecasting n: background, standard methods, and energy access applications

The development of accurate load forecasts is a challenge as old as industrial scale electricity production, however in recent decades - as computation has become cheaper - research efforts have broadened to include high resolution data-driven and methodological innovations. The literature contains numerous highly complete reviews of load forecasting research across scales and applications (e.g., [9]), so many so that the most recent [10] in fact proposes specific criteria for evaluating novelty of contributions within this dense landscape. Included in this list are new (1) problems, (2) methodologies, (3) techniques, (4) datasets, and (5) findings, though the authors are careful to highlight that *significance* must be judged relative to industry or commercially-relevant challenges [10]. The follow paragraphs outline state-of-the art from these perspectives in order to situate the current manuscript within the field. Forecasting has been most frequently applied for large scale grid applications on short time frames (hour, day, and week ahead) and specifically in developed economies, scenarios where aggregation provides some level of smoothing and economic motivators for forecasting accuracy are large (hundreds of thousands of dollars [11]). Allocation and sizing of generation capacity (for base, peak, and intermediate loads) was historically approached through the use of load duration curves (LDCs) derived from daily peak demand data on an electric grid [12], with capacity investments determined through medium term (months to years) estimation of the evolution of LDC shapes. Accurate, long-term high resolution forecasting of load profiles corresponding to the hourly-annual (8760) simulation format found in widely used typical meteorological year datasets [13] and in models for building energy performance [14] and renewable generation applications [15] is today usually of interest for any application with highly constrained economics or poorly constrained demand/generation characteristics. Small islanded power systems (the focus of this work) fall squarely into both of these categories, particularly renewable energy systems which on one hand suffer significant economic penalties when forced to run backup generators and on the other face high capital costs related to battery storage and high variability and uncertainty in demand characteristics (e.g., as tackled for wind systems by Dutta et al. [16]). For such applications, where dynamics of both demand and generation are sub-hourly, LDCs prove inadequate for engineering design and therefore high-resolution demand data and simulations are needed.

Analysis of smart meter data has provided significant insight into some industry specific load behaviors [17,18], but development of probabilistic load prediction models for electricity applications (needed especially for cases where historical data are lacking) has lagged significantly relative to other fields

[19]. Several novel, more generalizable approaches have been evaluated for creating probabilistic demand models, ranging from probabilistic behavior modeling [20,21] to representative load curves [22] to Bayesian approaches [23], based on numerous different techniques (hidden Markov models [17,20], time-varying splines [24], ARMA models [23,25], and machine learning algorithms [22,23]) and generating some successes and cross-cutting lessons (e.g., temperature dependence of demand curves [20,26]). Transferability of methods to new applications is, however, in many cases limited by (1) a necessity for large volumes of application-specific ground-truth data (e.g., for behavior modeling), (2) loss of information in statistical representation (e.g., representative load curves), (3) loss of information in time structure (e.g., time-invariant Bayesian approaches), or (4) computational constraints. Identification of the appropriate method for a particular application therefore requires navigating trade-offs that are dependent on the ease (and cost) of data collection, volatility of actual demand, strength of demand auto-covariance, etc.

In particular, research related to load forecasting for small rural energy systems (micro- or mini-grids) in developing nations has lagged due to a paucity of recorded demand data (some exceptions include [21,27]). This remains true in spite of increasing interest in the potential for achieving significant energy access in, e.g., Africa and India via renewable energy based minigrids, as well as the recognition that essential services in the health sector critically depend on access to both electricity and thermal energy for indoor climate control [2,4].

To help bridge this gap, this manuscript presents a long time-frame (years) probabilistic electricity load forecasting tool for use in optimized design and sizing of islanded energy systems for off-grid health care facilities, a challenge which to date has primarily been (with very limited success) using inventory methods for demand prediction [4]. The tool is calibrated with a novel multi-year dataset collected from sub-Saharan health clinics (electricity demand, indoor and outdoor temperature, solar insolation) for the specific purpose of load forecasting. Probabilistic demand forecasting is accomplished using a Bayesian approach (the underlying probability distribution function is estimated using collected high-re solution data) wherein auto-covariance of demand is neglected following results of [20]. Seasonal aggregation of data provides a first-order representation of temperature dependence of health clinic electricity demands, resulting in an algorithm for hour-by-hour demand estimation which, when combined with Monte Carlo methods, can provide volumes of calibration/validation data for islanded system design. In terms of novelty metrics identified by [10], this work presents both a new methodology and dataset which relate to a highly significant, and extremely understudied, application area.

1.3. Engineering design tools: dynamic simulation and building energy modeling

Engineering tools have been developed to aid designers and planners in the sizing, configuration and costing aspects of clinic renewable energy infrastructure upgrades [4] but may not explicitly integrate thermal loads into electrical demand scenarios. Standalone Building Energy Models (BEM) for deriving thermal demand (e.g., EnergyPlus, [14]) could be deployed to make up this gap, but these have two main drawbacks: (1) they are mainly geared towards urban buildings meeting construction codes and HVAC standards [28,29] whose assumptions may be violated in practice at existing health facilities, and (2) the high level of parametric complexity in these models (e.g., multiple zones with diverse HVAC options) is inconsistent with the relative austerity of as-built health centers in Africa. In contrast a simple tool is required for rapid assessments that scale across multiple sites. To address the shortcomings of existing tools we developed a rapid assessment BEM parameterized for typical health centers using architectural plans from Uganda and Lesotho for integration into a previously developed open source code (in Python, hosted at Github) [30] distributed energy dynamic simulation program named *uGrid* [27,31]. Importantly, this effort utilizes historically recorded electricity meter data for electricity demand as well as indoor and outdoor temperature measured at four representative health centers in Lesotho between 2014 and 2017 to calibrate and validate the model. This manuscript describes the case study clinics, presents data collection methods, develops a statistical approach for generating the key energy demand datasets required for hourly simulation, and uses experimental data to validate the clinic BEM via an optimization approach.

2. Health center building energy model

The long-standing practice of predicting thermal energy demand for buildings varies by application from simple to elaborate schema that generally use foundational heat transfer and thermodynamic physics-based approaches [32] and a wide variety of computational frameworks including traditional symbolic and numerical methods [33], optimization algorithms [34,35], artificial neural networks [36] and various means of validating the foregoing [37,38]. Predictive building energy models are a well-researched topic area with an extensive corpus of recent reviews [39-45]. In this work, a simple and rapid assessment tool is developed and applied to the specific health center building type featured throughout sub-Saharan Africa, with the goal of facilitating a global initiative toward infrastructure upgrades. This assessment tool is parameterized using a synthetic probabilistically-derived electricity demand dataset whose characteristics are generated from a novel long-term dataset relevant for these markets.

2.1. Boundary conditions

The thermal demand for heating or cooling of a health clinic depends on the building construction and its response to changes in external and internal conditions, including the gradient between outdoor and indoor temperature, air exchange, thermal inertia (heat capacity of the structure and contents of the building), and gains due to irradiance, occupancy, and energy consumed within the envelope (electricity used within the building effectively translates into heating). For the BEM an energy balance between heat gains and heat sinks for the building is calculated on a 30-min time step.

Heat transfer across the health clinic envelope is modeled by a two resistance and one-capacitance (2R1C) network (Fig. 1), where the envelope resistances are equivalent to the reciprocal of the heat transfer coefficient U and resistances and thermal capacity are adjusted by means of non-dimensional factors θ and φ accounting for the accessibility of the wall (or roof or foundation) thermal mass from both sides.

For the building outer shell, the total wall (or roof or foundation) resistance is comprised of conductive resistance and constant external and internal surface resistances linked to convection and radiation. If more than one layer is present, the resistances of each layer are summed, where R_{layer} is computed from its thickness and the material conductivity. For windows (single glazing) a heat transfer coefficient of 5.8 Wm^{-2} K^{-1} is used and the solar heat gain coefficient (accounting for the fraction of admitted incident solar radiation) is 0.86. The building envelope thermal capacity is a function of the material density, thickness, and specific heat. Eqs. (1)-(5) are applied to exterior walls, the foundation, and the roof; Table 1 lists structural resistances.

$$R_{wall} = R_{se,wall} + R_{t,wall} + R_{si,wall} \tag{1}$$

$$R_{t,wall} = \frac{e_{cb,wall}}{\lambda_{cb}} \tag{2}$$

$$U_{wall,ext} = R_{wall}^{-1} \tag{3}$$

$$AU_{wall,ext} = (A_{wall,ext} + \theta_{frame} + A_{window})\cdot U_{wall,ext} \tag{4}$$

$$C_{wall,ext,m^2[J/m^2K]} = Cp_{cb}\cdot\rho_{cb}\cdot e_{cb,wall} \tag{5}$$

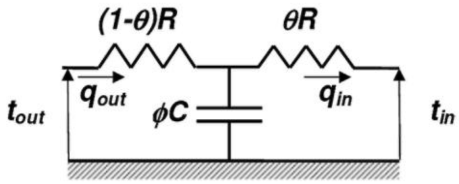

Fig. 1. *A 2r1c network applied to the building envelope with isothermal boundary conditions.*

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Table 1: *External and inner wall surface resistance in m^2 K W^{-1}.*

	R_{se}	R_{SI}
External wall	0.04	0.13
Roof	0.04	0.1
Floor	0.04	0.17

2.2. Heat transfer in walls, ceiling and foundation

For a given wall (roof or foundation) the following energy balances (Eqs. (6)-(8)) are applied:

$$\dot{Q}_{wall,out} \doteq \frac{A_{wall}}{R_{wall}\cdot(1-\theta)}\cdot(T_{out}-T_{wall}) \tag{6}$$

$$\dot{Q}_{wall,in} = \frac{A_{wall}}{R_{wall}\cdot\theta}\cdot(T_{wall}-T_{in}) \tag{7}$$

$$\dot{Q}_{wall,out}-\dot{Q}_{wall,in} = \frac{\partial U}{\partial\tau} = C_{wall}\cdot\phi\cdot\frac{\partial T}{\partial\tau} \tag{8}$$

Heat transfer across windows in the network model is assumed to be a single thermal resistance with no thermal mass:

$$\dot{Q}_{window} = AU_{window}\cdot(T_{out}-T_{in}) \tag{9}$$

Despite a general lack of mechanical ventilation systems, building air infiltration features prominently in typical sub-Saharan clinic construction in comparison to the increasingly airtight mode of construction followed in modern buildings more generally. Windows are frequently left open during clinic operation in warm weather, and outer doors are used throughout the day by patients. Therefore two separate Air Changes per Hour (ACH) factors are considered: 1.5 ACH during operating hours and 0.4 ACH during night time. The energy balance is calculated below (Eqs. (10) and (11)) using the air volumetric flow rate:

$$\dot{Q}_{inf} = \dot{V}_{inf}\cdot\rho_a\cdot C_{pa}\cdot(T_{out}-T_{in}) \tag{10}$$

$$\dot{V}_{inf}\,[\mathrm{m^3/h}] = ACH\cdot V_{in} \tag{11}$$

2.3. Internal and external heat gains

Internal thermal gains are created by occupants, lighting, and equipment. An average person outputs 70 W due to normal metabolism; an occupancy factor is applied to daytime (07:30-18:00) and night-time operation modes in the BEM (Fig. 2).

Total internal gains are a function of the occupancy and the electricity consumption (Eq. (12)):

$$\dot{Q}_{gains} = q_{occ}\cdot\dot{n}_{max,occ}\cdot\alpha_{occ} + \dot{Q}_{cons,el} \tag{12}$$

External heat gains consist of global horizontal irradiance (during daytime) absorbed across the areal footprint of the building modified by an absorption factor combining geometric and heat transfer effects (Eq. (13)):

$$\dot{Q}_{sun,in} = I_h A_{floor}\cdot\alpha_I \tag{13}$$

2.4. Energy balance

The heat transfers described above are illustrated in Fig. 3. The BEM calculates the indoor air temperature using an energy balance that includes a term for the internal thermal capacity (Eq. (14)). The heating loads are assessed by imposing a threshold-based regulation scheme that would maintain indoor temperature within selected values, for example set points that follow recommended standards [29,46,47] (i.e., 20 °C during working hours and 15 °C for non-working hours).

$$\dot{Q}_{wall,in} + \dot{Q}_{floor,in} + \dot{Q}_{roof,in} + \dot{Q}_{window} + \dot{Q}_{inf} + \dot{Q}_{sun,in} + \dot{Q}_{gains} + \dot{Q}_{heating} = \frac{\partial U}{\partial \tau} = C_{in} \cdot \phi \cdot \frac{\partial T}{\partial \tau} \tag{14}$$

It must be noted that to reasonably estimate the thermal demand of a health clinic the BEM must be parameterized with the geometry of the clinic, typical meteorological year (TMY) data for the location, and electricity consumption. Due to the relative importance of thermal inertia and solar irradiance absorption (primarily by uninsulated metallic roofing) in the BEM, factors adjusting for variation in the thermal capacitance of the external walls, internal walls and objects (furniture, equipment, etc.), irradiance absorption, and maximum occupancy are proposed as optimization variables for model validation (Table 2).

The BEM is then validated by optimizing the unknown parameters within bounds to obtain a solution representative of the building physics by minimizing the root mean squared error (RMSE) between predicted and measured indoor air temperature: $\sqrt{(T_{in} - T_{in,meas})^2}$. This is implemented using measurements from health centers in Lesotho, described in the following sections.

3. Case study health clinic data collection

Validation of the health clinic BEM uses information collected from various sources, including architectural drawings, surveys of operating health clinics, indoor and outdoor temperature measurements, and electricity meter data. For building characteristics, we observe that the construction materials used in the surveyed clinics in Uganda and Lesotho are concrete block outer and interior walls, concrete slab foundations, and a roof outer skin of corrugated steel supported by either wooden beams or steel trusses. An example section and floorplan of a standard clinic construction [48] is shown in Fig. 4.

The magnitude of energy demand will generally scale with patient catchment area, patient load, and floor plan of the clinic. In some jurisdictions, health centers are classified from level I to IV on the basis of services provided, and this will also coarsely correlate with energy demand. Patient loads (counts) at surveyed health centers were determined from records collected by clinic staff. Building areas were determined from site surveys or architectural drawings. Details of the surveyed clinics and the data collected at each are provided in Table 3.

3.1. Weather and electricity demand measurement

Five clinics of varying size and patient load were studied. Weather data, including indoor and outdoor temperature (Class B temperature accuracy ± 0.15 °C), were obtained with consumer grade wireless weather stations (PCE-FWS-20) with data-logging (30 min interval) capabilities. These were deployed by STG International at Khubetsoana and Lesotho Defense Force (LDF) clinics (Fig. 5). Electricity consumption at the Khubetsoana and LDF clinics were acquired and transmitted using GSM-enabled IOM-QEC1 class 1 utility meters (± 1% accuracy at full load) deployed by STG International, while electricity data from Maputsoe filter clinic was provided by the Lesotho Electricity Company via a Conlog utility billing meter. Electricity demand data from Man-emaneng clinic was provided by Partners in Health (PIH) using a Dent ElitePro XC power data-logger (± 1% accuracy), while the Kira health center data was acquired by STG International using a GSM-enabled Steamaco bitharvester equipped with an Eastron SDM120db class 1 single phase pulse meter (± 1% accuracy at full load).

3.2. Electricity demand profiles

In addition to using electricity data for insight into heat gain and validation of the BEM, electricity demand dynamics play a key role in engineering design of renewable energy systems to meet the needs of health clinics. It is therefore of dual utility to consider the synthesis of statistically valid demand dynamic datasets to enable rationalized health center energy system retrofit scenarios. To facilitate this, we present the hourly (8760) data for Maputsoe and LDF, two health clinics for which more than a complete year of data is available (Fig. 6) and extract seasonal and weekday/weekend daily load profiles for each of the five clinics surveyed, of which "summer" is shown in Fig. 7. The relevance of summer loads for these clinics is that the meter data is representative of electrical loads decoupled from thermal loads, asnone of the clinics surveyed used air-conditioning but several used electric heating during winter. Whereas Kira Health Center is equatorial (Uganda), the Lesotho health facilities in practice are subjected to increased lighting loads during winter months; for clinics with a grid connection, however, these loads are overshadowed by the significant energy demands for space heating.

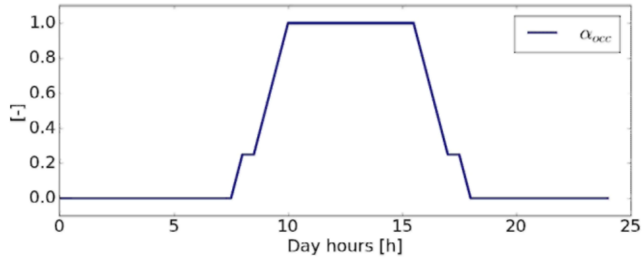

Fig. 2. Occupancy factor α_{occ}

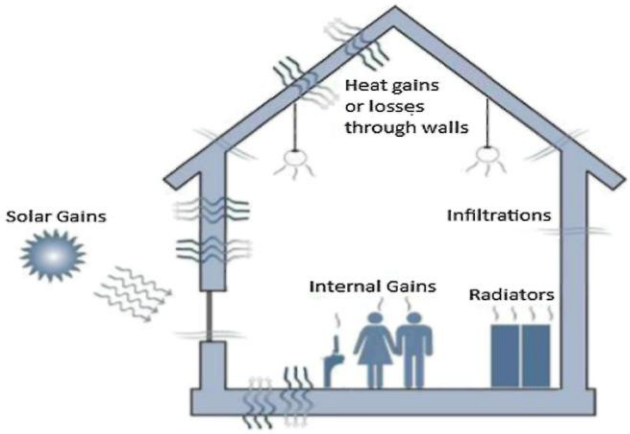

Fig. 3. Diagram showing heat sources and flows.

Table 2: Optimization variables and imposed ranges.

	Range
$\alpha C_{wall,ext}$	[1,8]
αC_{in}	[1, 10]
αI	[0.01, 0.40]
$n_{max,occ}$	[15, 35]

4. Building energy model (BEM) validation and results

Using indoor and outdoor temperature measurements combined with electrical load data collected at Khubetsoana and LDF health clinics, the parameters from Table 2 were optimized in Engineering Equation Solver using the integrated Genetic Algorithm (GA) function to minimize the sum of the squares of the difference between predicted and observed indoor temperature. Optimized parameters are presented in Table 4.

The quality of the BEM results is evaluated in a histogram plot of the error - (T_{BEM} - T_{meas}) - over the distribution (Fig. 8). Prior to optimization the BEM indoor temperature results are bimodal with a root mean squared error (RMSE) of 2.05 °C; after optimization 90% of the values are normally distributed between ± 2 °C, and the root-mean-square error is 1.33 °C. This RMSE is reasonable given the measurement accuracy of the weather stations. An excerpt of the comparison between modeled and predicted indoor temperature for the LDF clinic is shown in Fig. 9.

These results validate the thermal performance of the building envelope at the surveyed health centers, and the BEM parameters tuned in this study (Fig. 10) can therefore be used to predict thermal energy demand of other health centers with constructions similar to that described in Fig. 4 on the basis of readily accessible characteristics, namely floorplan area, meteorological conditions (TMY data), and electricity demand (measured locally or synthetically derived as per Section 4.1 below).

Typical Meteorological Year (TMY) data proximate to a health center of interest may be available from a variety of sources (e.g., [49]), however electricity consumption data are comparatively sparse. To bridge this gap we propose that a statistical approach can be used to synthesize health center electricity data on the basis of measurements taken at similar, proximate health centers.

4.1. Electricity demand synthesis from load measurement data

Dynamics in energy consumption patterns are a critical driver of performance in energy systems. In this study we demonstrate the development of synthetic health center electricity demand dynamics by means of cumulative distribution functions (CDFs) generated from the empirical probability density functions (PDFs) of measured load data across four seasons for operational hours of the day (0800-1600) and night (1700-0700), operational conditions identified as statistically distinct. These CDFs (shown for Maputsoe Filter Clinic in Fig. 11) can be used to generate synthetic demand data that is statistically representative of the load measurements at that location and monitoring period by generating a series of uniform random numbers on the interval [0,1] which are used to sample from the CDF. The PDF bin corresponding to the density contribution causing the CDF to surpass these values are then selected [50] (typically the exact value is randomly selected from an individualt bin using a uniform distribution). This approach generates datasets that can be paired with TMY data, enabling these two main drivers of electrical and thermal demand to be used for dynamic simulation (such as the BEM of this study), sizing, and performance models (such as *uGrid* [27] or HOMER [5]) on an hourly or more granular time step.

For the purposes of conducting a preliminary engineering design it can be expedient to synthesize electricity demand from known CDFs such as those in Fig. 11 for clinics where no nearby electricity data have been recorded. In such cases an approximate starting point can be achieved by extrapolation - across geographies, using scaling factors for differential clinic sizes or outpatient statistics, or temporally where full year data is lacking - provided that during the monitoring period the thermal fraction of demand is sufficiently decoupled from other uses that are not affected by variations in meteorology. Although we stress appropriate caution in relying on this approach, a second order polynomial correlation between average daily Outpatient Department (OPD) visits and average (non-HVAC) electricity consumption in kilowatt-hours (kW h) is developed for the five health centers investigated in this study in Fig. 12 and provided in Eq. (15) (R^2 = 0.999):

$$kWh_{ave,daily} = 6.62018123 + 0.173005244 \cdot OPD_{ave,daly} + 0.000234934713 \cdot OPD^2_{ave,daily} \quad (15)$$

Table 3: Location and details of surveyed Health Clinics including key metrics from measurement campaigns (2014-2017)

Country	Health Center	Latitude	Longitude	Area [m^2]	Average OPD Visits [pp day^{-1}]	Ave Daily Electricity Demand [kW h]	Peakload [kW]
Lesotho	Manemaneng	- 29.549407	28.9803	192	15	9.8	1.5
Lesotho	Khubetsoana	-29.286401	27.523262	425	110	27	11
Lesotho	Lesotho Defense Force	- 29.329236	27.475986	344	145	38	13.4
Lesotho	Maputsoe Filter Clinic	- 28.887406	27.910147	1140	450	132	33
Uganda	Kira HC III	0.397938	32.640427	315	55	16.5	4.4

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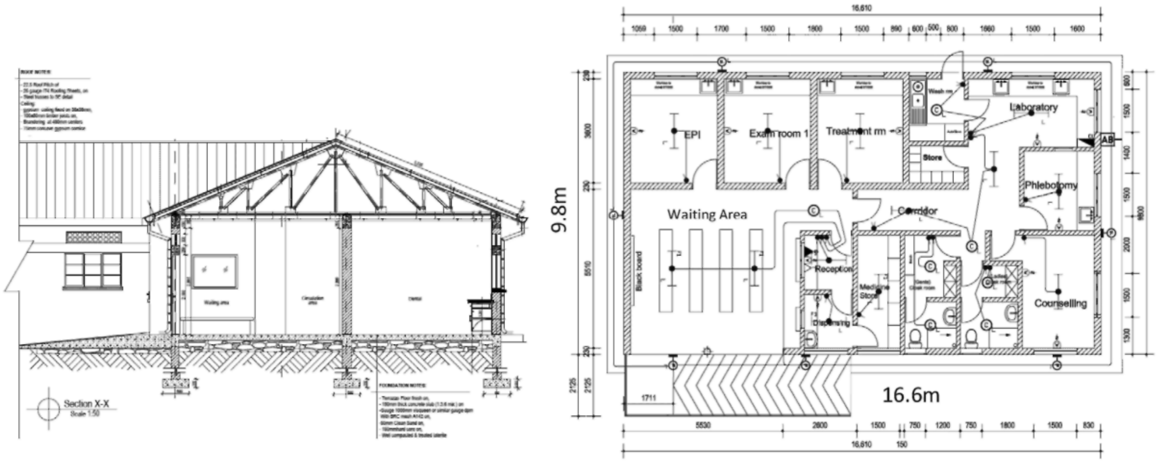

Fig. 4. Standard construction detail health center and floor plan from level III health center in Lesotho (from [48]).

4.2. Full-year dynamic simulation of electrical and HVAC loads at a health center

Using the tools and approaches developed for the BEM, including health center probabilistic electricity demand estimation, a designer can use the results of an annual simulation to specify the size and performance specifications of building energy systems to provide electricity, heating, and/or cooling to an existing or new construction health clinic. In addition to the parameters described in Section 3, the BEM can impose rule-based temperature control (analogous to the operation of a thermostat) for the clinic HVAC system. This includes selecting temperature set points for cycling on and off the HVAC during cooling or heating duty. A nominal range of comfort for human occupancy according to [29] is indoor temperature maintained between 20 and 27 °C, however in practice the user will have some intervention in the set points during actual operation, and the BEM has the flexibility to model dynamic temperature thresholds.

To demonstrate model functionality for an example clinic using TMY data, an annual simulation of HVAC demand at the LDF clinic is computed by solving the energy balance for the health clinic on an hourly time step with system thermal capacity set to 60 kW and heating and cooling temperature thresholds set respectively at 21-15 °C and 25-30 °C (day/night) (Fig. 13).

Fig. 5. Weather station installation at LDF health clinic by STG International staff (Makoanyane Khakhanyo).

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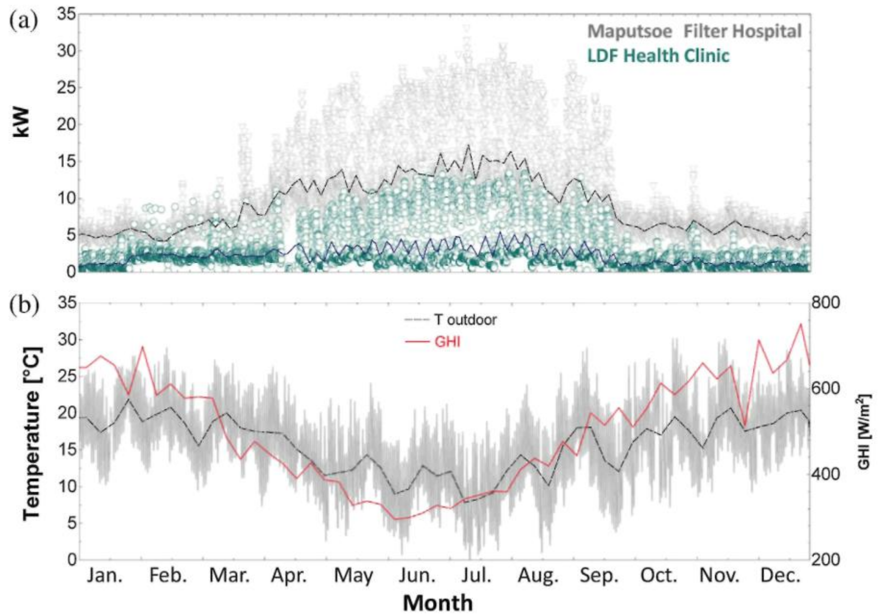

Fig. 6. (a) Hourly electricity load measured at Maputsoe (Gray) and LDF (Blue-Green) health clinics in Lesotho with weekly moving averages and (b) meteorology corresponding to measurements in (a) including Global Horizontal Irradiance (GHI) and ambient outdoor temperature.

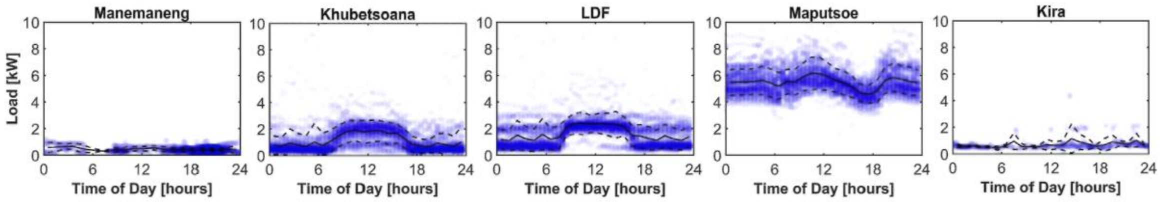

Fig. 7. Daily summertime load profile for five surveyed health clinics in Lesotho (first four) and Uganda (Kira), with lines showing average (solid) and 1 standard deviation (broken) load levels.

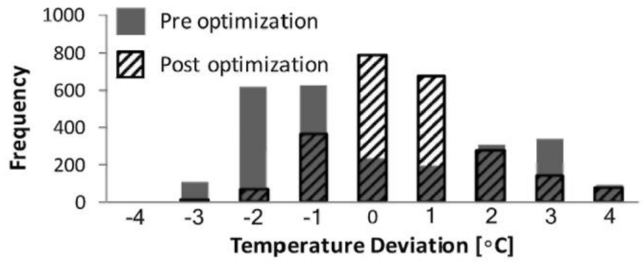

Fig. 8. Histogram of the temperature deviation between observed indoor temperature (PCE-FWS-20) and the predicted indoor temperature using the Building Energy Model of this study showing pre (solid) and post (diagonal pattern) validation using the four parameters in Table 2.

Table 4: Optimized parameters for clinic Building Energy Model

	Value
$\alpha C_{wall,ext}$	$1.170 \cdot 10^{8}$ [J/K]
αC_{in}	$7.236 \cdot 10^{7}$ [J/K]
αI	25%
$n_{max,occ}$	34 persons

This BEM can be used to estimate building envelope performance and thermal demand for HVAC at health clinics in various climates across a range of service levels and patient catchments as well as to simulate the impact and cost of deploying various HVAC technologies. For example, as a planning tool the thermal loads modeled at the LDF health clinic could be used to estimate the change in electricity consumption after installing a central heat pump to meet cooling and heating loads in comparison with existing resistive heating products. The BEM results for LDF show thermal energy demand of 54 $kWh{\cdot}m^{-2}yr^{-1}$ and 140 $kWh{\cdot}m^{-2}yr^{-1}$ for cooling and heating respectively. Assuming a typical Coefficient of Performance (COP) of 3 for a heat pump of 60 kW, the facility would require approximately 6 $MWh{\cdot}yr^{-1}$ of electricity for cooling and 16 $MWh{\cdot}yr^{-1}$ for heating, which, at an electricity tariff of approximately 110 $USD{\cdot}MWh^{-1}$ in Lesotho equates to an annual HVAC expenditure of 2400 USD or 7 $USD{\cdot}m^{-2}$. By comparison neglecting cooling and only heating the clinic with resistive (radiant or oil-filled) heaters (current practice) would cost 5280 USD per annum, or 15 $USD{\cdot}m^{-2}$ using the temperature thresholds set above. We note that relative humidity in occupied spaces should be maintained at below 65% to reduce the likelihood of conditions leading to microbial growth [46], however in this study we have only considered indoor thermal forcing and neglected conditioning of air or thermal demand for domestic hot water.

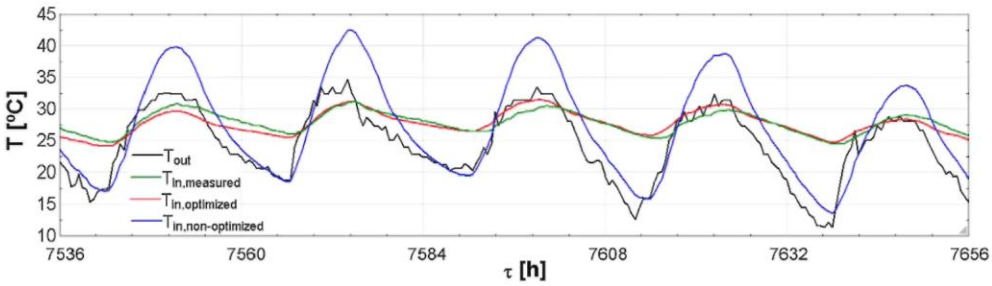

Fig. 9. An excerpt of five weekdays from the LDF Health Clinic for observed indoor (green) and outdoor (black) temperature, and the Building Energy Model predicted indoor temperature both pre (blue) and post (red) validation. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

5. Conclusions

Efforts to improve the level of service at health care facilities in sub-Saharan Africa are intensifying, and the use of energy, both electricity and thermal management of the indoor environment, plays a critical role in supporting vital functions in an institutional setting. While tools exist for engineering design and analysis of traditional hospital infrastructure, this study addresses important questions about the context of lower tier health clinics deployed in peri-urban and rural locations, namely:

• Considering the unique aspects of the materials and construction of African health clinics what are the impacts on building thermal performance and the implications for indoor climate control?

• Given the general lack of data for hourly electricity consumption in health clinics of varying size and OPD loads how can synthetic dynamic demand datasets be generated from existing measurements in a statistically valid way to support annual energy simulations?

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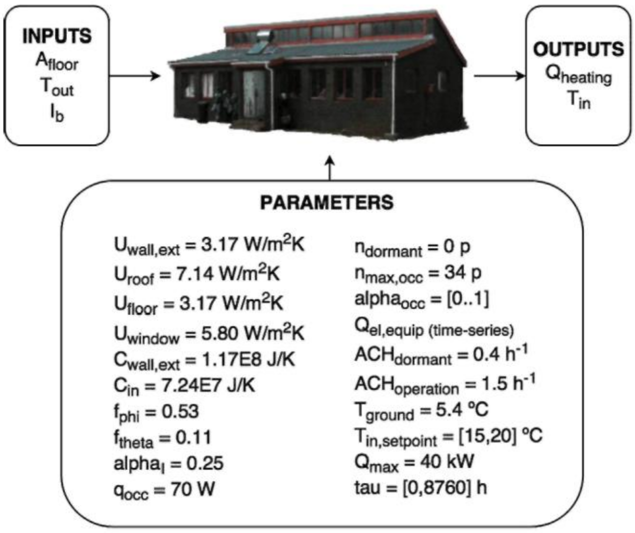

Fig. 10. Building Energy Model input and output variables

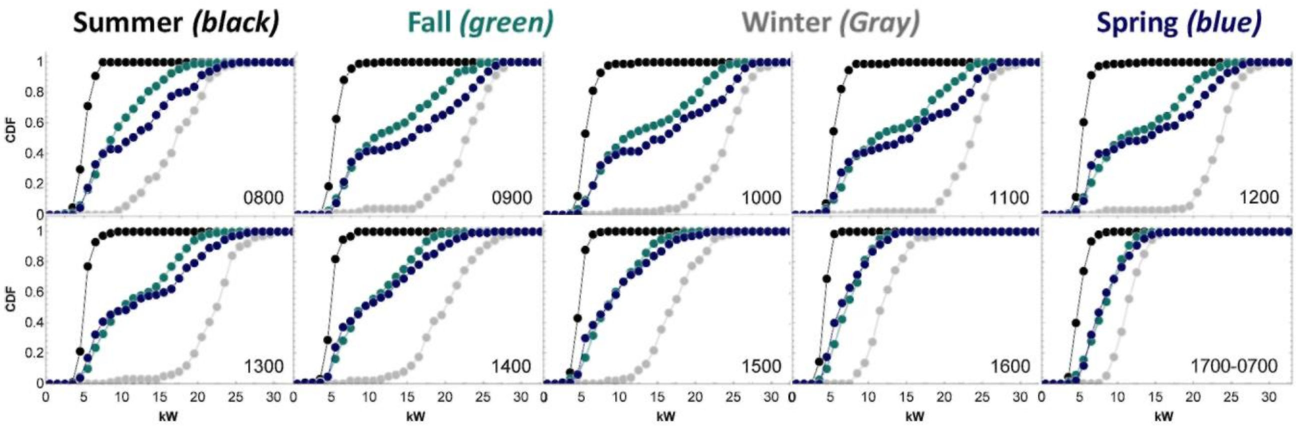

Fig. 11. Cumulative distribution functions (cdfs) for hourly electricity consumption at Maputsoe filter clinic, Lesotho, over four seasons.

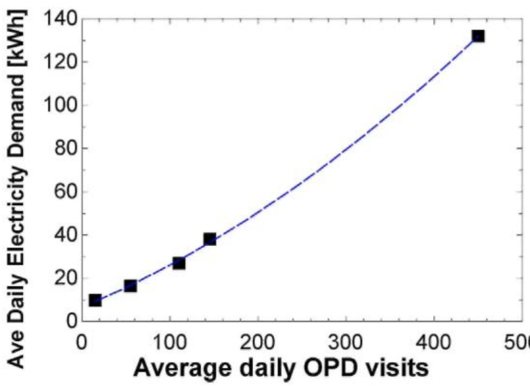

Fig. 12. Correlation between average Outpatient Department (OPD) visits and average daily (Non-HVAC) electricity consumption at five surveyed health centers.

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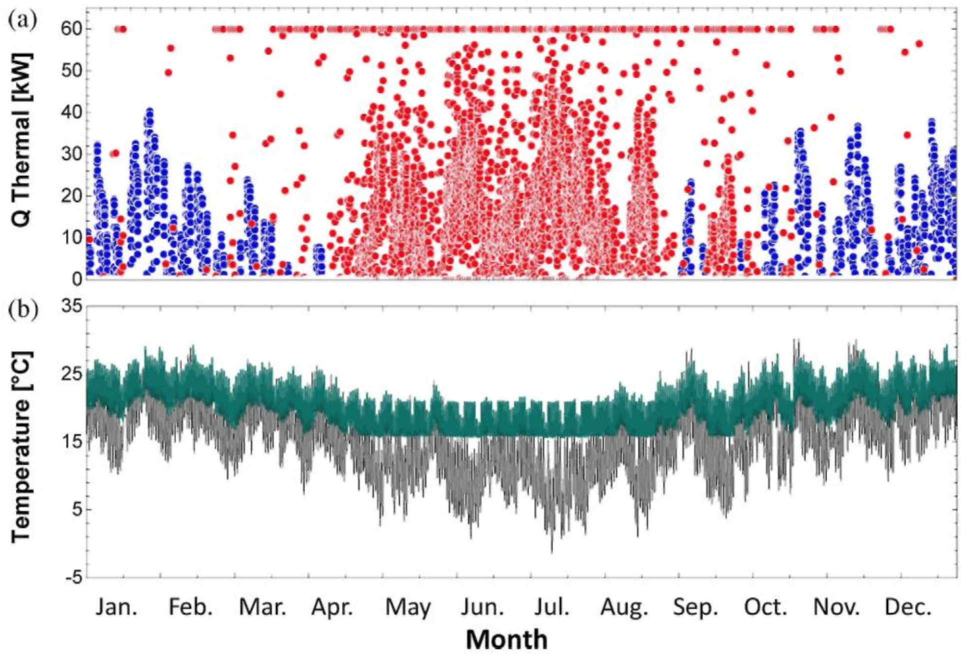

Fig. 13. (a) Modeled hourly heating (red) and cooling (blue) loads in kilowatts at the LDF Health Clinic in Maseru, Lesotho, and (b) outdoor temperature (gray) from Typical Meteorological Year data and indoor temperature (green) from rule based control of comfort levels. Note that the maximum capacity of the heat pump for supplying thermal injection or rejection is set to 60 kW on the basis of balancing between the capital cost of equipment and allowance for a two-hour temperature ramp on the coldest day of the year. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

The first question is addressed using an optimization method to determine the fitting parameters for an equivalent circuit thermal building energy model (BEM) validated with indoor and outdoor temperature measurements. The BEM is developed using a limited subset of known parameters, including the materials of construction, standard aspect ratios, user input for the floorplan area, and typical meteorological year (TMY) data for the location of the clinic of interest. The model follows a simple rule-based control logic analogous to thermostat temperature settings to maintain indoor air temperature between user input bounds and calculates the thermal energy requirements for heating and cooling the building envelope on an hourly time step. These data can be integrated to provide information on peak load (for capacity sizing equipment), energy use on an areal basis ($kWhm^{-2}yr^{-1}$), or operational costs with user input for HVAC equipment specifications (e.g., coefficient of performance) and the local electricity tariff.

The second question is addressed by means of a measurement campaign (from 2014 to 2017) using smart meters to establish time series of electricity use at five health centers (four in Lesotho and one in Uganda). The time series are binned hourly across statistically differentiated operational regimes (seasonally, weekday/weekend), and the probability density function is used to generate cumulative distribution function (CDFs) for the creation of synthetic electricity demand datasets valid for the measurement sites. The relationship between the magnitude of daily energy consumption (kWh) and a proxy for the activity level of the clinic - Outpatient Department (OPD) visits - is investigated.

The methodologies of this study are used in conjunction with the BEM to derive a complete perspective of the electricity and heating and cooling demand for an example health clinic, to predict the equipment size, electricity demand, and operational cost of energy. This design tool is intended to be deployed to enhance the quality and lower the cost of energy system assessment and engineering design of power generation and storage for supporting critical health care missions. In future work this model will be progressively improved through the addition of new validation temperature and electricity datasets from health centers representing a wide cross section of service delivery levels and geographies in sub-Saharan Africa.

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