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

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Abstract:

Simulation of energy and building HVAC demand is a core engineering discipline, but practical applications for design tend to focus on buildings within urban environments and with usage modes established according to indoor comfort standards meeting codes for best practices (e.g. ASHRAE). Rapid deployment of health services is underway to meet the growing needs of populations in sub-Saharan Africa, however an energy infrastructure to support high quality services has tended to lag. Understanding the energy needs of health centers constructed with local building methods and materials and operating outside of the jurisdiction of HVAC codes is complicated by a lack of experimental data. In this work we link the thermal envelope performance under heating and cooling loads with meteorological conditions and measured operational electricity demand. A resistance-capacitive type energy balance model is created using typical health center architectural data for sub-Saharan Africa (using floorplans from Uganda and Lesotho) and heat transfer characteristics, and energy flows between HVAC equipment, internal loads, and ambient conditions are simulated on an hourly timestep with indoor temperature thresholds. A typical meteorological year dataset for Lesotho is used as a case study and validated with indoor temperature measurements and power metering at four health center sites spanning a daily patient load ranging from 15-450 per day and rural and urban catchments. The development of this approach provides an important tool for planners interested in sizing and costing energy infrastructure to meet operational demand at health centers in both urban and rural areas of developing countries.

Keywords:

Africa, Health Center, Energy, Sustainability, Building Energy Model, Dynamic Simulation

1. 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 600m people that lack an electricity connection [1]. The expectation is that electrification contributes to the potential for positively impacting health outcomes through improved service delivery using modern equipment and procedures; meanwhile market forces have contributed to lowering the cost of e.g. solar panels and expanded the budgetary ability to deploy electricity at remote clinics. While new health centers that are built in unelectrified areas can incorporate renewable energy systems into their design, there is a far more extensive portfolio of facilities already built and operating without power that are candidates for retrofitting and upgrading. The sizing, configuration and costing of these retrofit energy systems depend critically on understanding the demand for energy in a health clinic setting.

1.1. Health center demand dynamics

The time variance of demand correlates with a number of factors such as size of the facility (footprint and patient load), its 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 (more commonly in heating) fuels such as LPG, coal, or biomass. The computational nature of a design tool is to perform an hourly simulation of energy system yield against an imputed demand dataset.

This implies knowledge of diurnal, weekly and seasonal variation in demand, data for which is typically unavailable. The synthetic construction of a demand dataset is often pursued using inventory based assessment methods [2] that fail to capture actual observed usage patterns [3].

1.2. Engineering design tools: dynamic simulation and building energy modelling.

Engineering tools exist to aid designers and planners in the sizing, configuration and costing aspects of clinic renewable energy infrastructure upgrades [4], but they may not explicitly integrate thermal loads into electrical demand scenarios. Standalone Building Energy Models (BEM) for deriving thermal demand could be deployed to make up this gap but these are mainly geared towards urban buildings meeting construction codes and HVAC standards [5], [6] whose assumptions may be violated in practice at existing health facilities. To address the shortcomings of existing tools we developed a BEM parameterized for typical health centers using architectural plans from Uganda and Lesotho for integration into a previously developed dynamic simulation program *uGrid* [7], [8]. Importantly, this effort utilizes meter data for electricity demand and indoor and outdoor temperature measured at four representative health centers in Lesotho between 2014-2017. This work describes the case study clinics, presents data collection methods, develops a statistical approach for generating the key energy demand datasets needed for hourly simulation, and uses experimental data to validate the clinic BEM via an optimization approach.

2. Health Center Building Energy Model

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 (the 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 translates effectively into heating). For the BEM an energy balance is calculated on a 30-minute timestep between heat gains and heat sinks for the building (this can be downsampled to hourly data as needed).

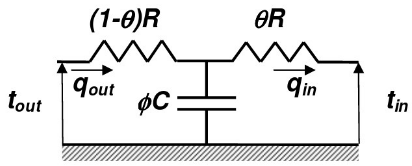

Figure 1 A 2R1C network applied to the building envelope with isothermal boundary conditions

Heat transfer across the health clinic envelope is modelled by a two resistances and one-capacitance (2R1C) network (Figure 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 resistance 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 W m_{-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's thermal capacity is a function of the material density, thickness and specific heat. Equations 1 to 5 are applied to exterior walls, the foundation and the roof and Table 1 lists structural resistances.

$$R_{wall} = R_{se,wall} + R_{t,wall} + R_{si,wall} \quad (1)$$

$$R_{t,wall} = \frac{e_{cb,wall}}{\lambda_{cb}} \quad (2)$$

$$U_{wall,ext} = R_{wall}{}^{-1} \quad (3)$$

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

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

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 (Equations 6-8) are applied:

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

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

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

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

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

Despite a general lack of mechanical ventilation systems, building air infiltration features prominently in 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 outside 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 nightime. The energy balance is calculated below using the air volumetric flow rate:

$$\dot{Q}_{inf} = \dot{V}_{inf} \cdot \rho_a \cdot Cp_a \cdot (T_{out} - T_{in}) \quad (10)$$

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

2.3. Heat gains

Internal thermal gains are created by occupants, lighting and equipment. An average person outputs 70W due to normal metabolism; and an occupancy factor is applied to daytime (0730-1800) and nightime operation modes in the BEM (Figure 2).

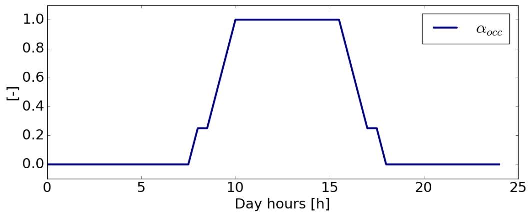

Figure 2 Occupancy factor α_{occ}

Total internal gains are a function of the occupancy and the electricity consumption:

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

2.3. Energy Balance

The heat transfers described above are illustrated in Figure 3 below. Using an energy balance that includes a term for the internal thermal capacity, the BEM can calculate the indoor air temperature. The heating loads are assessed by imposing a threshold based regulation scheme to maintain the indoor temperature within selected values, for example set points that follow recommended standards [6], [9], [10], i.e. 20°C during working hours and 15°C for non-working hours.

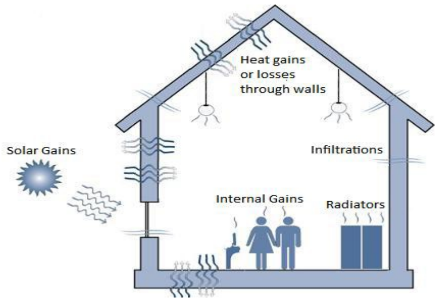

Figure 3 Diagram showing heat sources and flows

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

(13)

In order to predict the thermal demand of a health clinic the BEM should be parameterized with the geometry of the clinic, typical meteorological year (TMY) data for the location, and electricity consumption.

Table 2 Optimization variables and imposed ranges

	Range
$\alpha_{Cwall,ext}$	[1,8]
α_{Cin}	[1,10]
α_I	[0.01,0.40]
$n_{max,occ}$	[15,35]

The BEM is then validated by varying the unknown parameters for capacitances, absorbed irradiance, and maximum occupancy within bounds (Table 2) to obtain a solution that is representative of the building physics, by minimizing the error between predicted and measured indoor air temperature: $(T_{in}-T_{in,meas})^2$. This is pursued using measurements from health centers in Lesotho, described in the next 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 foundation, 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 from [11] is shown in Figure 4.

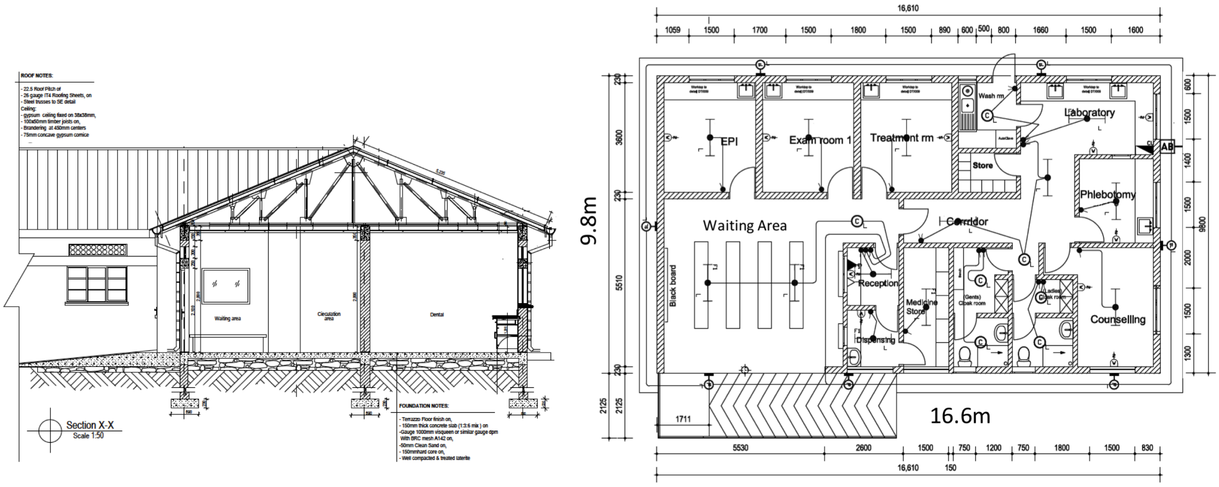

Figure 4 Standard construction detail health center and floorplan from level III health center from [11]

The magnitude of energy demand will generally scale with catchment areas, patient loads, and floorplan layouts of health clinics. In some jurisdictions, health centers are classified from level I to IV on the basis of services provided and this will generally correlate with energy demand. Patient loads at surveyed health centers were determined from records collected by the clinic staff. Building areas were determined from site surveys or architectural drawings. Details of the surveyed clinics and the data collected at each are shown below:

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

Country	Health Center	Latitude	Longitude	Area [m^2]	Average OPD Visits [pp day^{1}]	Ave Daily Electricity Demand [kWh]	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

3.1. Weather and electricity demand measurement

Weather data including indoor and outdoor temperature were obtained with consumer grade wireless weather stations (PCE-FWS-20) with datalogging capabilities deployed by STG International at Khubetsoana and Lesotho Defense Force (LDF) clinics. The logging interval used is 30 minutes. Electricity consumption at the Khubetsoana and LDF clinics are acquired and transmitted using GSM-enabled IOM-QEC1 class 1 utility meters deployed by STG International, while electricity data from Maputsoe filter clinic is provided the Lesotho Electricity Company via a Conlog utility billing meter.

Electricity demand data from Manemaneng clinic is provided by Partners in Health (PIH) using a Dent ElitePro XC power datalogger, 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.

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

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 relevant to consider the synthesis of statistically valid demand dynamic datasets for 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 (Figure 6), and extract "summer" daily load profiles for each of the five clinics surveyed. The relevance of summer loads for these clinics is that the meter data is representative electrical loads decoupled from thermal loads, as none of the clinics surveyed used air-conditioning, but several used electric heating during the wintertime. Whereas Kira Health Center is equatorial the Lesotho health facilities in practice are subjected to increased lighting loads during wintertime; these loads however are overshadowed by the significant heating loads at clinics with a grid connection.

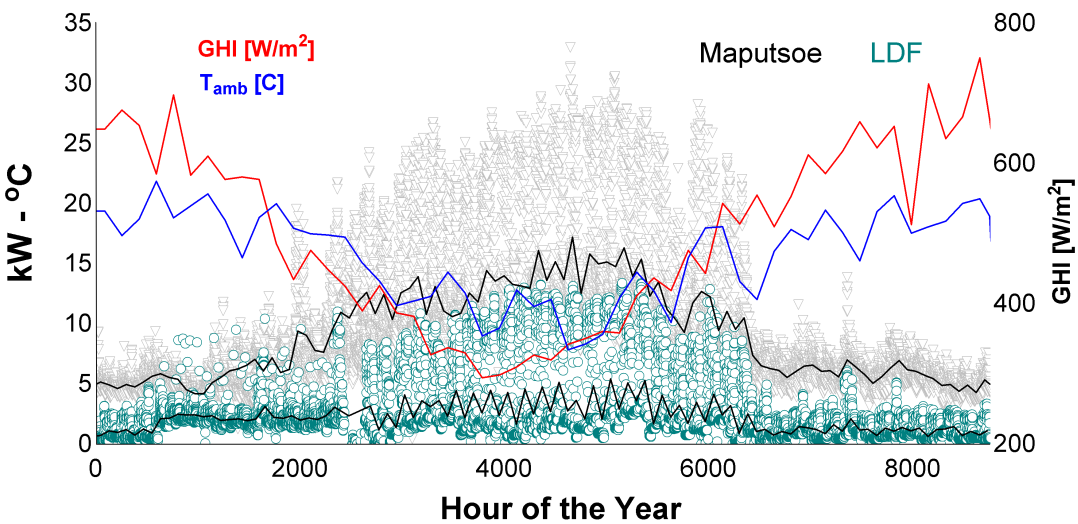

Figure 6. Hourly electricity load measured at Maputsoe (Gray) and LDF (Blue-Green) health clinics in Lesotho with weekly moving averages and an overly showing Global Horizontal Irradiance (GHI) and ambient outdoor temperature

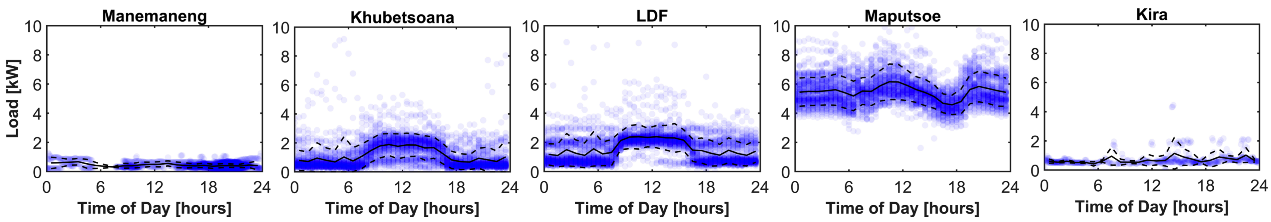

Figure 7 Daily summertime load profile for five surveyed health clinics in Lesotho and Uganda, with lines showing average (solid) and 1 standard deviation (broken) load levels.

4. Building Energy Model validation and results

Using indoor and outdoor temperature measurements combined with electrical load data collected at Khubetsoana and LDF health clinics, the BEM system of equations was implemented and 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. The obtained global optimum was achieved with the parameters presented in Table 4.

Table 4. Optimized parameters for clinic Building Energy Model

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

The quality of the BEM results is evaluated in a histogram plot of the error - $\sqrt{((T_{BEM}-T_{meas})^2)}$ – over the distribution (). 90% of the values fall between ±2 and the root-mean-square error is calculated at *RMSE* = 1.33 °C, which is reasonable given the measurement error of 1°C on the weather stations. An excerpt of the comparison between modelled and predicted indoor temperature for the LDF clinic is shown in.

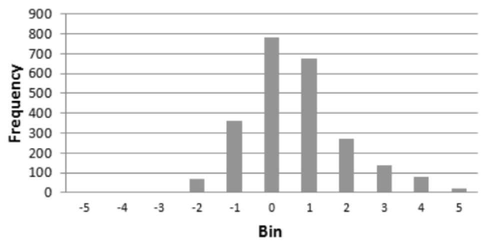

Figure 8. Histogram of the temperature deviation between observed indoor temperature (PCE-FWS-20) and the predicted indoor temperature using the Building Energy Model of this study

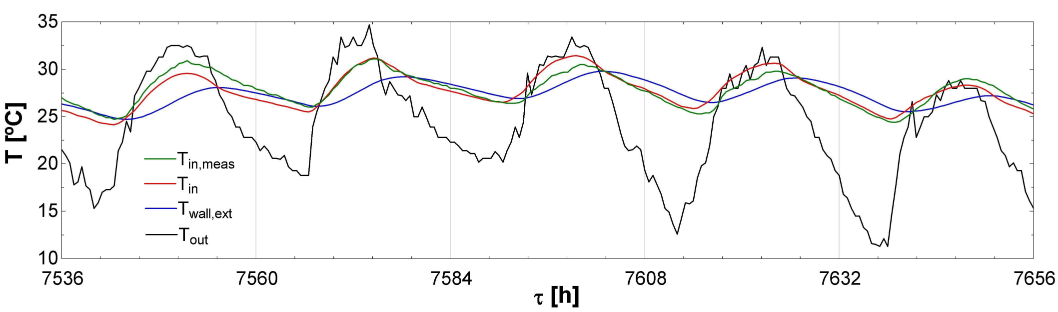

Figure 9. An excerpt of five weekday values from the LDF Health Clinic for observed indoor (Green) and outdoor (Black) temperature, and the Building Energy Model predicted indoor temperature(Red) and wall temperature (blue) from this study

These results validate the thermal performance of the building envelope at the surveyed health centers, and the parameters tuned in this study can be used in the BEM to predict thermal energy demand on the basis of readily available characteristics of a health center, namely its floorplan area, data regarding the meteorological conditions of the site (TMY data) and electricity demand .

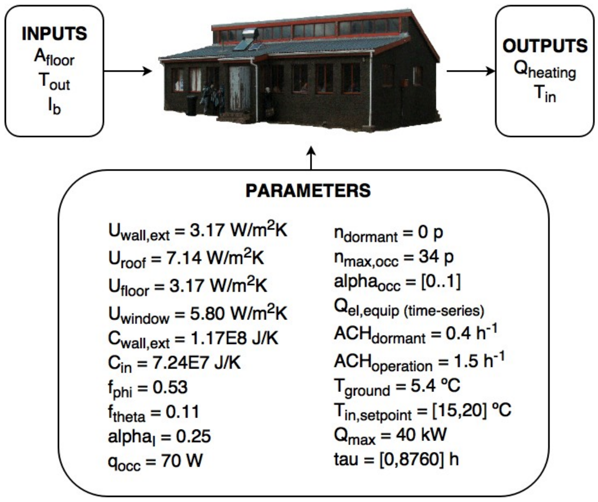

Figure 10. Building Energy Model input and output variables.

Typical Meteorological Year data proximate to a health center of interest may be available from a variety of sources such as e.g. [12] however electricity consumption data is comparatively sparse. It is also conceivable that a program objective to predict health center thermal energy demand is concurrent with prediction of electricity demand for example during the planning stage of new construction or a contemplated energy system upgrade on an existing on-grid or off-grid clinic. In this case 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 probability density functions (PDFs) of measured load data across four seasons for operational hours of the day (0800-1600) and nighttime (1700-0700). These CDFs (shown for Maputsoe Filter Clinic in Figure 11) can be used to generate synthetic demand data that is statistically representative of the load measurements at that location and monitoring period. This approach can used to generate paired datasets with TMY data where the main drivers of electrical and thermal demand can be used for dynamic simulation (such as the BEM of this study) and sizing and performance models (such as *uGrid* [13]) on an hourly or more granular timestep.

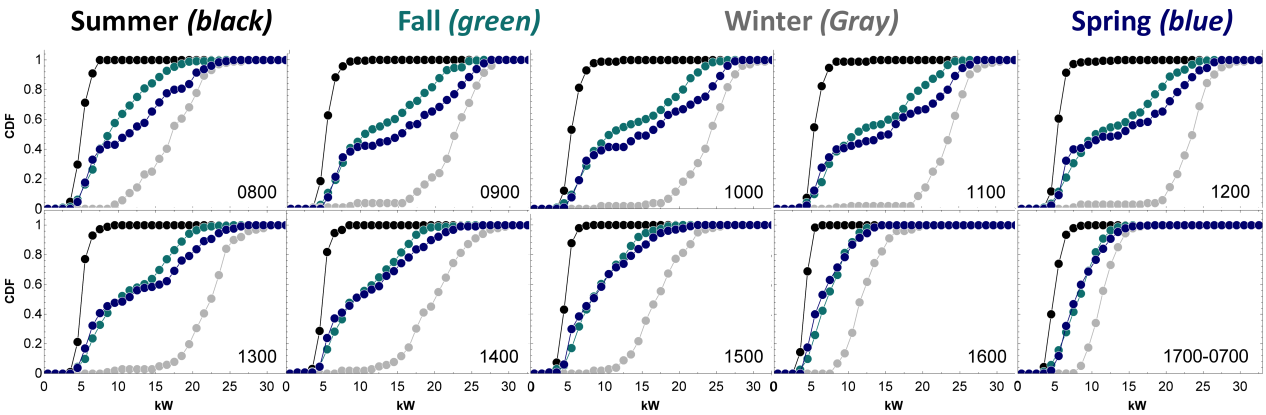

Figure 11. Cumulative Distribution Functions for hourly electricity consumption at Maputsoe filter clinic, Lesotho, over four seasons

Although we stress appropriate caution in doing so, for situations where a lack of data to inform design is a hindrance (as it can be in many location in sub-Saharan Africa), it can be possible in a preliminary engineering design to assess electricity demand from known CDFs such as those in Figure 11 which are extrapolated across geographies, using scaling factors for differential clinic sizes, and extrapolating 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). For the five health centers investigated in this study a second order polynomial correlation between average daily Outpatient Department (OPD) visits and average (non-HVAC) electricity consumption in kilowatt-hours is illustrated in and shown below in ($R^2 = 0.999$):

$$kWh_{ave,\ daily} = 6.62018123 + 0.173005244 * OPD_{ave,daily} + 0.000234934713 \cdot OPD_{ave,daily}{}^{2} \qquad (1)$$

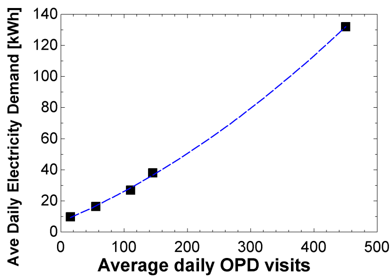

Figure 12. Correlation between average Outpatient Department (OPD) visits and average daily (Non-HVAC) electricity consumption at five surveyed health centers

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 envelope of building energy systems to provide electricity, heating and cooling to an existing or new construction health clinic. In addition to the parameters described in section 3, the BEM will necessarily impose a rule-based control analogous to the operation of a thermostat for the clinic HVAC system. This includes selecting temperature setpoints for cycling on and off the HVAC during cooling or heating duty. A nominal range of comfort for human occupancy according to [6] is indoor temperature maintained between 20-27°C, however in practice the user will have some intervention in the setpoints during actual operation, and the BEM has the flexibility to model dynamic temperature thresholds. To demonstrate this 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 timestep with system thermal capacity set to 60kW, heating temperature thresholds set at 21-15°C, and cooling thresholds set at 25-30°C during daytime and night time respectively (Figure 13).

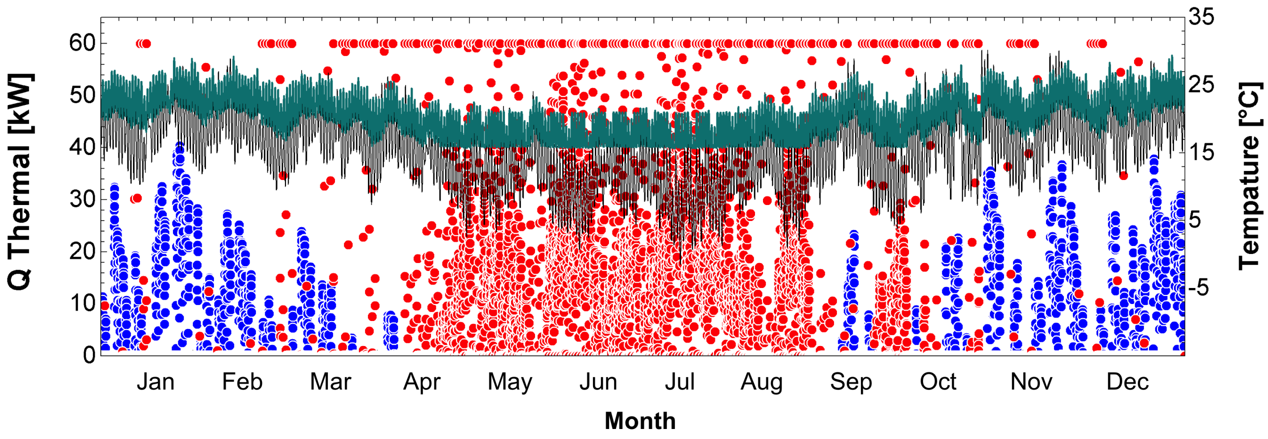

Figure 13. Modelled heating (red) and cooling (blue) loads in kiloWatts at the LDF Health Clinic in Maseru, Lesotho, with outdoor temperature (gray) from Typical Meteorological Year data and indoor temperature (green) from rule based control of comfort levels. Note that the maximum capacity of the heat pump for supplying thermal injection or rejection is set to 60kW, 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.

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, and simulate the impact and cost of deploying various HVAC technologies. For example, as a planning tool, the thermal loads modelled 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 m^{-2} yr^{-1} and 140 kWh m^{-2} yr^{-1} for cooling and heating respectively. Assuming a typical Coefficient of Performance (COP) of 3 for a heat pump of 60kW, the facility would require approximately 6 MWh yr^{-1} of electricity for cooling and 16 MWh yr^{-1} for heating, which, at an electricity tariff of approximately 110 USD MWh^{-1} in Lesotho equates to an annual HVAC expenditure of 2400 USD or 7 USD 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 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 microbrial growth [9], however in this study we have only considered indoor thermal forcing and neglected conditioning of air or thermal demand for domestic hot water.

5. Conclusion

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 hospital infrastructure in a traditional setting, 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 on hourly electricity consumption in health clinics of varying size and OPD loads, how can dynamic demand datasets be generated in a statistically valid

way to support annual energy simulations?

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 and standard aspect ratios, and 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 timestep. These data can be integrated to provide information on peak load (for capacity sizing equipment), energy use on an areal basis (kWh m^{-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 2014-2017) 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 and the probability density function is used to generate cumulative distribution functions (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 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 can be deployed to enhance the quality and lower the cost of energy system assessment and engineering design for supporting critical health care missions, and can in future work 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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Nomenclature

α	Absorbance
A	Area

I_b Beam irradiance
k Thermal conductivity
$\dot{Q}$ Heat flow
τ Time
U Overall heat transfer coefficient
$\dot{V}$ Velocity

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