PARAMETERISATION OF INTERNAL LOADS IN ASSESSMENT OF BUILDING ENERGY PERFORMANCE

Rebecca Ward[1], Ruchi Choudhary[1], Yeonsook Heo[2], Adam Rysanek[3]
[1]Cambridge University Engineering Department, Cambridge, United Kingdom
[2]Cambridge University Department of Architecture, Cambridge, United Kingdom
[3]Institute of Technology in Architecture, ETH Zürich, Switzerland

ABSTRACT

In a computational building energy model internal loads are characterized by user-defined peak values, multiplied by diversity factors that simulate the typical daily change in use. For an existing building, while a detailed energy audit may be undertaken, attaining accurate internal load profiles for every space of the building can be prohibitive. In reality, the variation of internal loads over time is inherently stochastic. In order to develop a stochastic model of building operations, a number of studies have proposed parameterisations that incorporate some estimation of variability, with different assumptions and levels of complexity. This paper aims to examine potential models and thereby identify possible parameterisations for a stochastic model of internal loads in a building with quantification of uncertainties in inputs.

INTRODUCTION

A building energy model relies on accurate input of internal loads to facilitate a realistic simulation of the energy balance within a building. It is well known that building energy consumption simulated at the design stage rarely agrees with observed data post-design, and with increasing deployment of energy monitoring systems this so-called 'performance gap' is becoming increasingly visible (de Wilde, 2014). It would be expected that simulation of an operational building would result in forecast consumption in closer agreement with reality, yet it is still notoriously difficult to match the simulation to the observed data (Sun, 2014). One fundamental cause of the gap is the inadequacy of current approaches to definition of occupancy-related demand; while the models themselves can be demonstrated to predict energy demand adequately given an accurate specification of internal loads, it is difficult to define occupant-related internal loads accurately, even in fully operational buildings (Page et al., 2008).

As yet there are few comprehensive validation and verification studies of occupancy-related factors (Ryan and Sanquist, 2012), but it is known that small power demand (plug loads) can make a significant contribution to the total; the BEES phase 1 pilot study indicates that for mixed retail/food outlets small power demand is approximately 40% of total electricity consumption (DECC, 2013). The value was difficult to quantify, however; the suggested value was obtained from the difference between metered data and a bottom-up analysis, suggesting that a better bottom-up analysis might facilitate greater understanding of the demand.

This study has concentrated on parameterisation of small power demand i.e. plug loads; four different approaches have been identified. The paper compares the alternative parameterisations with the aim of maximising confidence in the simulation output while minimizing the effort required to generate the input. Recognising that complexity necessary in the design of parameterisation may be due to the quantity of interest pertinent to a design problem, the outcome of the different parameterisations have been compared to a range of key performance indicators (KPIs) and the uncertainty associated with the key parameters for each different parameterisation has been investigated.

The four approaches range from simple aggregation of demand to fully stochastic simulation. Within the simplest models it is assumed that there is different weekday/weekend power demand which fluctuates between peak and off-peak values (estimated from benchmarks, literature, or measured) according to the weekday or weekend time schedule (Building Research Establishment, 2010). More complexity may be added by assigning different schedules and demand profiles to different device types and hence building up an aggregate demand load; this is the 'bottom-up' deterministic approach (Menezes et al., 2014). Aggregating the demand like this may mis-represent an essentially stochastic load, however (Page et al., 2008); whether this is significant may depend on the KPIs of interest. The DELORES model (Rysanek and Choudhary, 2015) aims to retain the stochastic nature of the demand by generating a fully stochastic 365 day/24 hour demand profile. An alternative way to generate a stochastic demand, advocated by Sun (2014), is via a statistical analysis of monitored data.

The four models have been applied to a case study building and results are presented for KPIs extracted for both blind and calibrated simulations. The discussion summarises the benefits and uncertainty quantification of each model.

DESCRIPTION OF MODELS

Dynamic simulation models are used routinely at the design stage to predict the operational energy consumption of a building. In order to define operational power demand, guidelines such as the National Calculation Method (Building Research Establishment, 2010) may be consulted, by which one standard activity is assigned to each building space. This defines the small power demand in terms of a nominal value and schedule, and electricity consumption is summed over the year according to the schedule. For a typical office, peak power demand is stated as 11.77 W/m^2 and the peak time period is from 7am until 7pm, weekdays only (off-peak power consumption is 0.63 W/m^2).

Recently, an alternative approach has been proposed. Following CIBSE TM54 (CIBSE, 2013) a designer would estimate annual power demand based on the expected number of devices, average device power demand and average annual operational hours. By disaggregating annual operational hours, weekly and daily consumption may be derived. CIBSE TM54 recommends that engineers 'present the results as a range', but the extent of the range is unspecified; typical values for average power demand, together with 'average', 'conservative' and 'highly conservative' heat gains from desktop computers and monitors are given in CIBSE Guide F (CIBSE, 2012).

The advantage of these simple approaches are that they require a small number of objective parameters and consequently allow consistency in simulation across a portfolio of buildings. However, this strength is also their weakness; the results are applicable only for 'typical' use profiles, and if use deviates significantly from the norm, the results may be misleading.

Bottom-up Deterministic Model

Menezes et al (Menezes et al., 2014) suggest two parameterisations for plug loads;

- Model 1: random sampling of monitored data
- Model 2: bottom up model.

In Model 1, daily power demand profiles at 1 minute intervals are randomly selected from a database of monitored data for each equipment type. The process is repeated 30 times and a Student's t-distribution is used to calculate upper and lower prediction limits. This model avoids the need for assumptions regarding the expected usage profile of individual items of equipment provided that the items monitored are representative of the entire population; however the approach relies heavily on monitored data which are not typically available.

Model 2 is an alternative, bottom-up, approach which extends CIBSE TM54 by specifying operational power demand in more detail, with an estimate of the uncertainty associated with the calculation. Energy consumption is estimated based on the the quantity, power demand and usage of each type of device. Operation times are defined by 'strict' and 'extended' switch-on and switch-off times as detailed in Table 1. Table 2 presents typical power demand values for computers (Menezes et al., 2014). Device state is characterised as 'off', 'low' or 'on', corresponding to a specified power demand for each state. Each device is assigned one of four possible usage profiles, which specify the hours for which the equipment is considered to be in the 'on' state; the four usage profiles relate directly to the operation times, and are are termed 'strict', 'extended', 'always on' or 'transient', where 'transient' equates to being in the 'on' state for 50% of the time period corresponding to 'strict' switch-on and switch-off times. Estimates of the number of devices switched off at the end of each day and the expected drop in power demand at lunchtime are also specified. Finally, Menezes specifies a usage diversity factor which accounts for the difference in usage between the week and weekend. This *usage* diversity factor should not be confused with the hourly diversity factors used by ASHRAE (Abushakra et al., 2001) which encompass the usage diversity factor and usage profile specified in the Menezes model.

The hourly power demand, Q can be summarised by the following equation;

$$Q = Q_{base} + d \sum_{i=1}^{4} p_i \Delta q_i \qquad (1)$$

where Q_{base} is the base load, d is the usage diversity factor, i is the usage profile (i.e. 'transient', 'strict' etc.) and p_i and Δq_i are respectively the proportion and the power demand above the base load of devices assigned to usage profile i, according to that usage profile for the hour of interest. The stochastic nature of the demand is bounded by specifying a +/- 10% variation on the usage diversity factor, d.

The benefits of such a bottom-up approach are that there is no reliance on detailed monitoring data, although expert judgement is required to define the subjective parameters.

Table 1: Menezes: Operational Parameters

Usage diversity factor, d	Weekday	75%
	Weekend	15%
Switch-on Time	Strict	09:00
	Extended	08:00
Switch-off Time	Strict	17:00
	Extended	19:00
Lunchtime	Start	12:00
	End	13:00

Bottom-up Stochastic Model

Another approach which uses a 'bottom-up' summation of equipment power consumption is DELORES, presented in Rysanek and Choudhary (2015). In this model, device state is again characterised by the power demand in the 'on', 'low' or 'off' states, but here the stochasticity is simulated directly: transition probabilities are assigned to the state of each device in each hour, dependent on its prior state and the time period of the day. Each day is divided into three time periods, corresponding to 'peak', 'off-peak' and 'rest' times; the three states and three daily time periods therefore

Table 2: Menezes: Model Parameters

Device	Proportion		Power Demand (W)			Usage profile (% of equipment)			
	(%)	State:	Off	Low	On	Strict	Extended	Always On	Transient
High-end desktop	14		1	80	150	30	30	25	15
Low-end desktop	16		1	30	40	70	10	10	10
Laptop	71		1	20	30	30	40	0	30
19” screen	85		0	1	25	50	30	0	20
21” screen	15		0	1	45	50	30	0	20

require 27 transition probabilities as illustrated in Table 3. The state of each device is calculated in each hour of the year from its state in the previous hour and the probability of transition using a Markov Chain Monte-Carlo simulation. The stochastic nature of the model results in different daily profiles each day which aims to mimic the likely variation in daily profile typically observed over time.

A nominal time schedule defines the hours that correspond to the daily time periods, with a specified allowable potential deviation from this nominal schedule. The transition probabilities and nominal schedules are defined for weekdays, Saturdays and Sundays and potential holidays are accounted for by estimating the probability in a given month that any day will be a holiday. Example parameters for a desktop computer weekday operation are detailed in Table 3; corresponding weekend transition probabilities are given in (Rysanek and Choudhary, 2012).

The model can be summarised by equation 2:

$$Q = \sum_{j=1}^{N} q_j(s(T, s-1, \mathbf{P})) \tag{2}$$

i.e. the hourly power demand, *Q* is equal to the summation over *N* devices of the power demand of each device, q_j in state *s*, where *s* is a function of the time period of the day, *T*, the prior state, *s*-1, and the matrix of transition probabilities, **P**.

Data-Driven Model

A number of studies have assessed the potential for prediction of future energy consumption based on prior monitored consumption data, using some form of statistical analysis (Amber et al., 2015). The study by Sun (2014) takes this approach further and predicts the uncertainty surrounding future energy predictions based on existing data. The basic equation for the Sun model is simply:

$$Q = q_p D \tag{3}$$

i.e. the hourly power demand, *Q* is equal to the product of the peak hourly demand, q_p and a diversity factor, *D*, which varies hourly, as distinct from the weekday/weekend usage diversity factor, *d*, specified in the Menezes model.

Sun used empirical data from a series of 16 buildings analysed under ASHRAE Research Project 1093-RP (Abushakra et al., 2001). The annual peak hourly demand, q_p, was identified from the data for each building and characterised as a normal distribution. Mean hourly weekday and weekend electricity consumption were extracted from monitored data, and used to derive the hourly diversity factor, *D*. The mean weekday/weekend hourly data were collated into a 48hr matrix, and the mean and covariance of that matrix were calculated to be used as input for generation of random 48hr vector profiles assuming a multivariate normal distribution.

In generating a full covariance matrix it is inherently assumed that there is correlation between the energy consumption in one hour and in any other hour. Sun concluded that a reduced covariance matrix was more appropriate in which only the diagonal and immediately adjacent terms are retained, implying correlation only between the energy consumption in adjacent hours.

Parameter Uncertainty

Uncertainty in simulation outcomes is a factor of the uncertainty in the model parameters. This is not comprehensively included in any of the models considered here. For parameters such as device power demand, the simulation outcome is directly proportional to the specified parameter values. This is alluded to in the CIBSE TM54 approach which suggests using a range of possible power demand values to establish upper and lower bounds. Uncertainty in operational parameters is more difficult to quantify; attempts have been made, for example the usage diversity factor within the Menezes model is subject to a +/- 10% variation in order to generate upper and lower bound power demand, and the specification of possible deviation from the daily schedule in DELORES simulates the uncertainty in transition times between daily time periods. For the Menezes model, uncertainty in the distribution and usage profiles of different devices is only significant if the power demand for each device under each usage profile is significantly different. Uncertainty in the daily schedule of time periods is simulated within DELORES but not in the Menezes model; the impact of incorporating this uncertainty would be to increase variability in the timing of the transition between operational states. In DELORES the choice of transition probabilities can have a variable impact dependent on where the simulation is operating within the distribution of power states i.e. the Markov chain converges to a stationary distribution of states, but the route and rate

Table 3: DELORES: Weekday transitional probabilities for office computer

		Prior Operating State								
		Peak 08:00-17:00			Off-peak 17:00-21:00			Rest 21:00-08:00		
		On	Low	Off	On	Low	Off	On	Low	Off
Next Operating State	On	0.90	0.80	0.87	0.50	0.25	0.05	0	0	0
	Low	0.07	0.16	0.03	0.25	0.50	0.05	1	1	0
	Off	0.03	0.04	0.10	0.25	0.25	0.90	0	0	1

of convergence will depend on the starting conditions. The parameters may be standardised across buildings or building-specific, measurable or requiring expert input ('subjective'). A simple categorisation of the main parameters for these models in terms of their applicability, measurability and uncertainty is proposed in Table 4; in the table a scoring system has been used where 0 indicates 'No', 2 indicates 'Yes' and 1 indicates 'Possibly' i.e. the parameter may be inferred from monitored data, but is not directly measurable.

As will be demonstrated in the following sections, with the exception of the NCM model the simulation results exhibit upper and lower bounds; it must be stressed that these bounds do not encompass all the uncertainties, as indicated in Table 4.

MODEL APPLICATION

The models have been applied to a case study of the Ashby Laboratory, at Cambridge University Engineering Department, UK. This is a graduate student office, 916m^2 in area, comprising 5 self-contained professorial/administrative offices together with a large open-plan space intended to accommodate up to 84 students. The space is sub-metered for plug loads which arise primarily from the use of desk-top/laptop computers and associated monitors. Drawings are available which indicate the notional floor layout, however the actual floor layout is somewhat different in terms of desk positioning and orientation. For the purposes of this analysis the term-time elecricity consumption attributable to small power demand has been analysed, using data from October 2013 to December 2014.

'Blind' Simulation

To ascertain whether using an alternative approach such as the Menezes model or DELORES would give a better estimate of the uncertainty than the NCM model at an early design stage, the models have been run 'blind' i.e. the model parameters given in the literature, and detailed previously in this paper, have been used in conjunction with the notional floor/desk layout to generate electricity consumption profiles. The notional floorplan indicates that there are a total of 93 computers in the space, assumed to be desktop computers for the DELORES model, but distributed between 'high-end' and 'low-end' desktops and notebooks for the Menezes model according to the distribution in Menezes et al. (2014). Small power electricity consumption has been assumed to be entirely attributable to computing, as the proliferation of computers subsumes all other consumption within this space. The Sun model has not been used for this blind comparison, as although the original model is based on data from a selection of buildings which could be considered to be comparable, the data comprises aggregate lighting/small power loads and disaggregation is not possible. It is also noted that the use of DELORES in this 'blind' study may not adhere to the simulation process recommended by its creators. They suggested that a blind simulation of objects in an unknown setting should be driven by calibrated transitional probabilities obtained from prior 'expert'-driven analyses of similar cases. The literature-derived transitional probabilities for a desktop computer found in Rysanek and Choudhary (2012) do not appear to have been subject to such scrutiny.

All model outputs have been compared against the monitored electricity consumption data for October - December, 2015.

Figure 1 illustrates the mean 48hr profile of electricity consumption for the models and the measured data, where the first 24hrs represents a mean weekday and hours 25-48 represents a mean weekend day. Figure 2 shows the predicted spread, i.e. interquartile range, of the results over the 48hrs. There are a number of points immediately apparent from the figures.

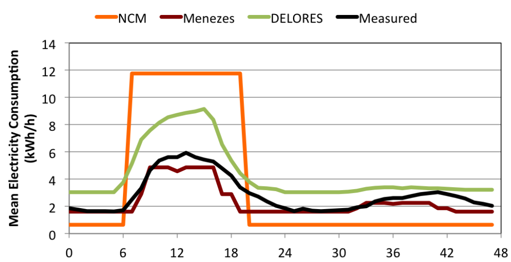

Figure 1: Mean Electricity Consumption, Blind Simulation

- The NCM model overpredicts the electricity consumption substantially during the week. This is a potential problem as it can lead to oversizing of cooling equipment. The model also underestimates the weekend electricity consumption which could be due to operational factors

Table 4: Characterisation of Parameters

Model	Parameter	Building-specific	Measurable	Uncertainty included in model
NCM	Power demand in each time period	0	n/a	0
	Daily schedule	0	n/a	0
CIBSE TM54	Power demand in each time period	2	1	2
	Daily schedule	2	1	0
Menezes	Power demand per state per device	0	2	0
	Proportion of devices assigned to each usage profile	2	1	0
	Proportion of devices switched off at night	2	2	0
	Daily schedule for each usage profile	2	1	0
	Usage diversity factor	2	1	2
DELORES	Power demand per state per device	0	2	0
	Daily schedule	2	1	2
	Transition probabilities	2	1	0
Sun	Peak hourly power demand	2	2	2
	Diversity factor	2	2	2

0=No, 1=Possibly, 2=Yes

i.e. a graduate studies office may be used more at the weekends than a commercial office.

- The DELORES simulation generally overpredicts whereas the Menezes model underpredicts the electricity consumption.
- More significant is the spread of the results; the +/-10% variation in deversity factor incorporated into the Menezes model gives a much lower spread and potentially a false level of confidence in the results, particularly when the consumption value is low.
- The NCM model does not include a prediction of the spread of the results; if misinterpreted, this could lead to over-confidence in the simulation outcome.
- DELORES is the only model to simulate the stochastic variability of the spread in the results.

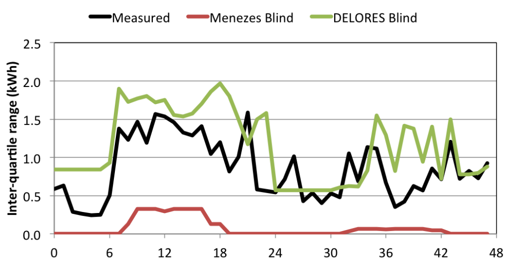

Figure 2: Electricity Consumption Inter-Quartile Range, Blind Simulation

Calibrated Simulation

If operational energy consumption data are available for a building, the Sun model may be used. It is also possible to calibrate the bottom-up Menezes and DELORES models to improve the simulation outcome. The calibration process depends on the quantity of interest; here the 48hr mean electricity consumption profile for 2 weeks in October 2013 was used as a basis for the calibration, with the process comprising the following steps;

- Quantify baseload and apportion type/state of devices to match baseload
- Quantify mean daily peak load and apportion types/state of devices to match peak
- Adjust notional schedules to match observed time profile

This is a straightforward process for the deterministic Menezes model. For the stochastic DELORES model, calibration requires adjustment of the transition probabilities and it is possible only to infer net transition probabilities from the monitored data. The nature of the Markov Chain approach used in DELORES means that the distribution of operational states converges to a stationary distribution over time, dependent on the transition probabilities and the starting distribution. So for a given baseload, it is necessary to ensure that the model converges at night to a distribution which matches the baseload. Calibrating the peak necessitates ensuring convergence to the right distribution at the right time of day, whereas the 'off-peak' period corresponds to a transition from the state distribution at peak electricity consumption to a satisfactory starting distribution for the night period. In this study, the process is simplified as only a single type of device has been assumed; calibrating transition probabilities for multiple device types could become increasingly unmanageable as the number of device types increases.

The post-calibration parameters used for the Menezes and DELORES models are given in Table 5 and Table 6. The device power demand values are the same as used in the blind simulation for each model.

The results of the models calibrated against data for the first 2 weeks in October 2013 are compared against the monitored data for October - December 2014 in Figures 3 and 4. A much closer agreement with the

Table 5: Menezes: Calibrated Model Parameters

Equipment type	Proportion (%)	Usage profile (% time)			
		Transient	Strict	Extended	Always On
High-end desktop	30	30	20	35	15
Low-end desktop	20	20	70	10	0
Laptop	50	30	30	40	0
19” screen	70	20	50	30	0
21” screen	30	20	50	30	0

Table 6: DELORES: Calibrated Weekday Transitional Probabilities

		Prior Operating State								
		Peak 08:00-14:00			Off-peak 14:00-22:00			Rest 22:00-08:00		
		On	Low	Off	On	Low	Off	On	Low	Off
Next Operating State	On	0.8	0.1	0.29	0.85	0.05	0	0.61	0.02	0
	Low	0.2	0.3	0	0.15	0.62	0	0.39	0.93	0
	Off	0	0.6	0.71	0	0.33	1	0	0.05	1

mean measured data is demonstrated. The Sun model, based on monitored data from October 2013, exhibits a similar variability in the spread to the measured data, which suggests that the data used for the calibration is reasonably representative of the electricity consumption from October - December 2014.

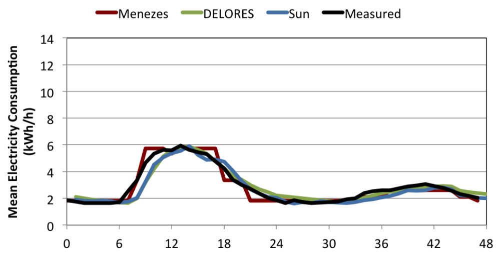

Figure 3: Mean Electricity Consumption, Calibrated Simulation

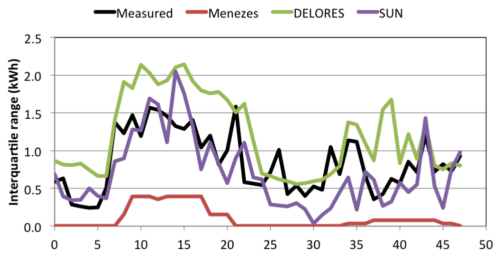

Figure 4: Electricity Consumption Inter-Quartile Range, Calibrated Simulation

Key Performance Indicators

While the mean profiles and spread are an interesting indicator of the comparability between the simulated and measured electricity consumption, it is comparison of the predicted Key Performance Indicators (KPIs) which provides a more useful insight. The KPIs considered here are the daily peak, the timing of the daily peak, the daily total and the weekly total electricity consumption values. The peak hourly electricity consumption is compared against the measured data for the blind and calibrated simulations in Figures 5 and 6. Figure 5 reiterates Figure 1, illustrating the over-prediction of DELORES and the under-prediction of the Menezes model. The calibrated models show much better agreement, with the Sun model demonstrating the closest agreement.

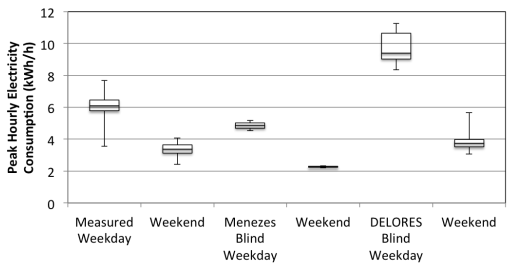

Figure 5: Peak Hourly Electricity Consumption, Blind Simulation

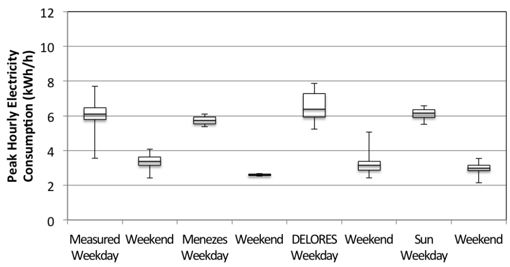

Figure 6: Peak Hourly Electricity Consumption, Calibrated Simulation

The only models which purport to simulate the timing of the peak are the Sun and DELORES models. Figure 7 shows the probability distribution of the peak hourly electricity consumption predicted by the blind DELORES simulation, compared against measured data. The predicted peak occurs later in the day for a weekday and a much less defined peak is predicted at the weekend than observed. Once calibrated the model predictions are better (Figure 8). Both models predict a narrower distribution than observed at the weekend, indicating that the distribution in the calibration data is narrower than that in the test data. The agreement with the weekday data is good, however. The total daily and total weekly electricity consumption results are illustrated in Figures 9 to 12 and show similar features with the exception that DELORES is closest in terms of the median value, while the Sun model range envelopes the measured values. It is interesting to note that aggregation of data can mask overprediction of weekday and underprediction of weekend energy consumption.

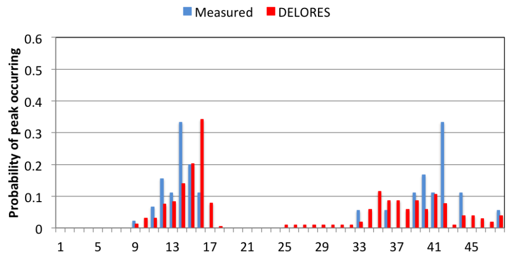

Figure 7: Timing of Peak, Blind Simulation

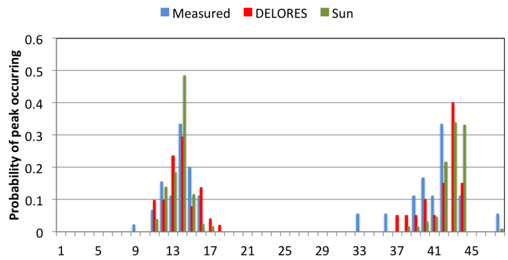

Figure 8: Timing of Peak, Calibrated Simulation

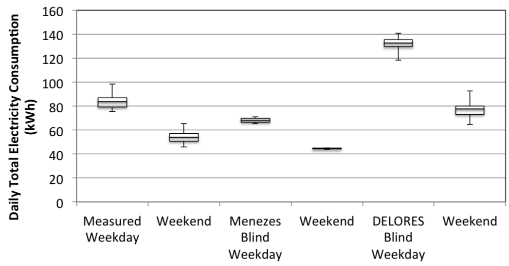

Figure 9: Total Daily Electricity Consumption, Blind Simulation

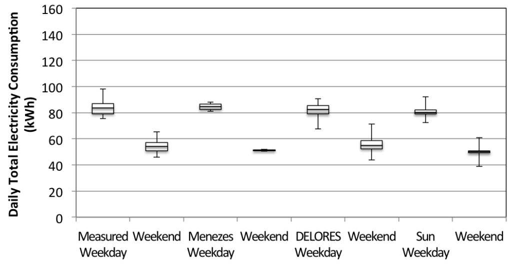

Figure 10: Total Daily Electricity Consumption, Calibrated Simulation

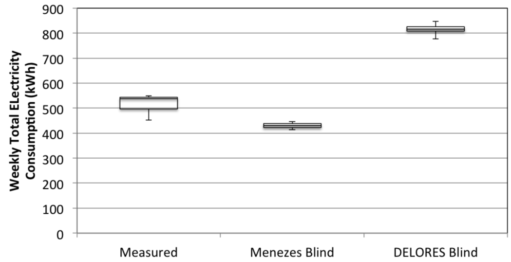

Figure 11: Weekly Total Electricity Consumption, Blind Simulation

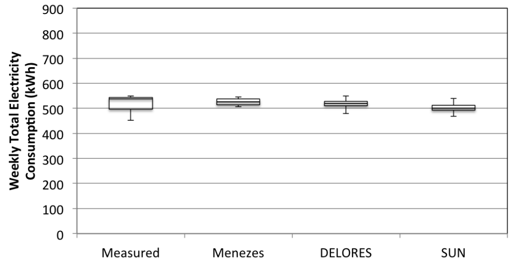

Figure 12: Weekly Total Electricity Consumption, Calibrated Simulation

DISCUSSION

The purpose of this analysis was to investigate which, if any, model offers the best approach for simulating plug loads in order to generate power demand profiles for input into a dynamic simulation model. The models differ in their approach and all have potentially useful features depending on the purpose of the simulation. An adequate simple model is to be favoured over more complex approaches. The simplest model used here, namely the NCM model, overpredicts weekday and underpredicts weekend demand for our case study. While the NCM model offers little possibility of variation, the CIBSE bottom-up approach lends itself to representing a more realistic annual demand; however disaggregating this demand to daily or hourly consumption will only provide an estimate of the mean.

The availability of monitored data facilitates data-driven models or calibration of bottom-up models. Provided the sample data is representative, a data-driven model will give a good estimate of future consumption. However, the model resilience is low; by comparison, calibration of a bottom-up model offers the facility to simulate change in use and hence offers greater resilience. The peak daily energy consumption can only be simulated using a model which embraces the stochasticity of the demand, as other models predict a uniform daily maximum. This is significant if prediction of the timing of the peak is of interest; DELORES and the Sun model give a good estimate of the time of day at which the peak occurs. The Sun model is limited to prediction based on past history, whereas DELORES is able to encompass operational change provided there is sufficient understanding of the impact of that change on the transition probabilities. With the exception of the NCM model, all of the models give some indication of upper and lower bound energy consumption. These bounds are not necessarily comparable; the Menezes model solely incorporates variation on the usage diversity factor, the DELORES bounds are generated from the stochasticity of the device state, while the the Sun model uses previous data to generate a possibility space from within which random electricity consumption profiles are drawn, enabling upper and lower bound results to be extracted.

For a model to be comprehensive in its treatment of uncertainty, it would need to include uncertainty in both measurable parameters, such as device power demand, and the more subjective operational parameters such as usage profile and time schedule. Uncertainty in the operational parameters is hard to define but may be as significant as measurable uncertainty depending on the KPIs; it may be best defined via a process of expert elicitation combined with inference from monitored data. However, the transition probabilities which characterise the DELORES model are difficult to infer with certainty from monitored data; uncertainty analysis of MCMC methods has been studied in some depth in the medical field (Ades and Cliffe, 2002), (Welton, 2005), and a suggested approach is to identify the possibility space for the transition probabilities from monitored data and to perform sensitivity studies which explore this space.

CONCLUSIONS

Four proposed parameterisations of plug loads suitable for input into a dynamic simulation model have been assessed as regards their applicability to the prediction of electricity consumption of a space subject to operational change. It has been found that by using monitored electricity consumption data it is possible to use any of the four approaches to create a calibrated model capable of predicting future power demand to a reasonable level of accuracy, provided the calibration is appropriate and robust. It is less clear which model is appropriate for 'blind' simulation; the difficulty of making 'blind' predictions with any degree of confidence has been demonstrated. In addition, the applicability of a model is dependent on the Key Parameter of Interest; if aggregate power consumption is the KPI then an aggregated approach is sufficient, however to identify peaks some measure of the stochasticity is required. Future studies will address which model is the simplest to parameterise for a wide range of applications and will investigate parameter optimisation.

ACKNOWLEDGEMENTS

The support of EPSRC is gratefully acknowledged.

REFERENCES

Abushakra, B., Sreshthaputra, A., and Haberl, J. S.and Claridge, D. E. 2001. *Compilation of Diversity Factors and Schedules for Energy and Cooling Load Calculations, ASHRAE Research Project 1093-RP, Final Report*. Energy Systems Laboratory.

Ades, A. and Cliffe, S. 2002. Markov Chain Monte Carlo estimation of a multiparameter decision model: Consistency of evidence and the accurate assessment of uncertainty. *Medical Decision Making*, 22:359 – 371.

Amber, K., Aslam, M., and Hussain, S. 2015. Electricity consumption forecasting models for administration buildings of the uk higher education sector. *Energy and Buildings*, 90:127–136.

Building Research Establishment 2010. *National Calculation Methodology modelling guide (for buildings other than dwellings in England and Wales)*.

CIBSE 2012. *CIBSE Guide F: Energy Efficiency in Buildings*.

CIBSE 2013. *CIBSE TM54: Evaluating operational energy performance of buildings at the design stage*.

de Wilde, P. 2014. The gap between predicted and measured energy performance of buildings:a framework for investigation. *Automation in Construction*, 41:40–49.

DECC 2013. DECC non-domestic building energy use project phase 1.

Menezes, A., Cripps, A., Buswell, R., Wright, J., and Bouchlaghem, D. 2014. Estimating the energy consumption and power demand of small power equipment in office buildings. *Energy and Buildings*, 75:199–209.

Page, J., Robinson, D., Morel, N., and Scartezzini, J.-L. 2008. A generalised stochastic model for the simulation of occupant presence. *Energy and Buildings*, 40:83–98.

Ryan, E. and Sanquist, T. 2012. Validation of building energy modeling tools under idealized and realistic conditions. *Energy and Buildings*, 47:375–382.

Rysanek, A. and Choudhary, R. 2012. A decoupled whole-building simulation engine for rapid exhaustive search of low-carbon and low-energy building refurbishment options. *Building and Environment*, 50:21–33.

Rysanek, A. and Choudhary, R. 2015. DELORES - an open source tool for stochastic prediction of occupant services demand. *Journal of Building Performance Simulation*, 8:97–118.

Sun, Y. 2014. *Closing the building energy performance gap by improving our predictions*. Georgia Institute of Technology.

Welton, N. 2005. Estimation of markov chain transition probabilities and rates from fully and partially observed data: Uncertainty propagation, evidence synthesis and model calibration. *Medical Decision Making*, 25:633 – 645.