Estimating the energy consumption and power demand of small power equipment in office buildings

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ABSTRACT
Small power is a substantial energy end-use in office buildings in its own right, but also significantly contributes to internal heat gains. Technological advancements have allowed for higher efficiency computers, yet current working practices are demanding more out of digital equipment. Designers often rely on benchmarks to inform predictions of small power consumption, power demand and internal gains. These are often out of date and fail to account for the variability in equipment speciation and usage patterns in different offices. This paper details two models for estimating small power consumption in office buildings, alongside typical power demand profiles. The first model relies solely on the random sampling of monitored data, and the second relies on a ‘bottom-up’ approach to establish likely power demand and operational energy use. Both models were tested through a blind validation demonstrating a good correlation between metered data and monthly predictions of energy consumption. Prediction ranges for power demand profiles were also observed to be representative of metered data with minor exceptions. When compared to current practices, which often rely solely on the use of benchmarks, both proposed methods provide an improved approach to predicting the operational performance of small power equipment in offices.

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1. Introduction
As buildings become more energy efficient, small power equipment such as computers are an increasingly significant source of energy end-use [1]. A study published by the New Buildings Institute suggest that plug loads can represent up to 50% of the electricity use in buildings with high efficiency systems [2]. Office buildings are likely to have higher cooling demands in the future due to climate change, emphasising the need to better understand (and reduce) the impact of internal gains from IT equipment [3].

Predicting internal heat gains accurately is of great importance in order to ensure that building systems are designed and operated as efficiently as possible. The use of nameplate electrical power ratings significantly overestimates the internal heat gains, which results in the specification of chillers with a higher capacity than needed [4]. This can result in increased capital cost as well as higher operating costs through longer periods of inefficient part load operation [5]. Nevertheless, detailed estimates of small power consumption are rarely undertaken and designers often rely on published benchmarks in order to account for small power demand in office buildings [6]. A review of published benchmarks for small power demand and consumption undertaken by the authors revealed that these are sparse, often out of date and broadly unrepresentative of small power equipment currently being used in UK office buildings [7]. Overall, the approach of using benchmarks inherently fails to account for the variability of small power loads in different buildings, presenting an additional shortfall.

This paper presents two methods for estimating building specific small power energy consumption. The study also aims to evaluate the associated power demand profiles, which can be used to inform predictions of internal heat gains. Focus is mainly on the use of computers as these are often observed to be the single biggest source of energy use amongst small power equipment [8,9]. Both models also account for the energy consumption of other small power equipment commonly found in offices such as screens, printers, photocopiers and local catering equipment. The first model relies solely on the random sampling of detailed monitored data,
minimising the need for assumptions regarding the operational characteristics of small power equipment. A second model was developed using a bottom-up approach, allowing for the expected power demand and usage profiles for different equipment types to be characterised.

2. Literature review

The widely referenced Energy Consumption Guide (ECG) 19 provides typical and good practice benchmarks for office and catering equipment electricity consumption (Table 1) [10]. Values are provided for four different types of office buildings: Type 1, naturally ventilated cellular office; Type 2, naturally ventilated open-plan office; Type 3, air-conditioned standard office; and Type 4, air-conditioned prestige office (typically including large catering kitchen and/or regional server rooms). Given the broader scope of the guide, which deals with all end-uses in office buildings, the four building types provided relate mainly to the way in which the building is conditioned. From a small power perspective however, such classifications are not necessarily adequate, as the energy consumption and power demand of small power equipment is not directly related to the way in which the building is conditioned. Nonetheless, these benchmarks highlight the variability in energy consumption for small power equipment amongst office buildings.

ECG 19 also provides benchmarks for power load density, varying from 10 to 18 W/m². These values can be used to estimate the electricity consumption when coupled with the number of run hours (daily, monthly, annually, etc.). More commonly, however, power load density is used to assess expected peak power demand, commonly being used to calculate internal heat gains, affecting the design of cooling systems. According to the Building Services Research and Information Association (BSRIA), a value of 15 W/m² can be used to represent typical small power load in general offices [11]. Conversely, a study conducted by the British Council for Offices (BCO) demonstrated that higher loads are found in typical office buildings, with one third of the offices monitored having installed loads higher than 15 W/m² [6]. The recently updated CIBSE Guide F suggests that a benchmark figure for building loads of 25 W/m² is adequate for most office buildings (with 15 W/m² when diversity is taken into account) [12]. The updated Guide F also suggests that when occupancy details are known, using a loading of approximately 140–150 W/desk might be a more appropriate approach.

High-level benchmarks are informative, but they need to be used with caution and in the right context as they fail to account for variations in diversity of use, workstation density, power management settings on ICT devices and the type of activity carried out in an office building. In an attempt to address such variations, CIBSE Guide F provides an alternative methodology for calculating installed loads based on a ‘bottom-up’ approach [12]. This method was adapted from Energy Consumption Guide 35 [13], and enables a more robust prediction of power demand and energy consumption. It relies on detailed information regarding the expected types and quantities of small power equipment, typical power consumption figures, power management settings, usage diversity and typical hours of operation for each equipment type. As a manual calculation however, this methodology is quite laborious and designers often resort to high level benchmarks instead. The new CIBSE TM54 proposes a simpler calculation based on the expected power demand and operating hours of individual desks/workstations, accounting for communal appliances separately [14]. This approach allows for variations in equipment specification and intensity of use to be accounted for, yet usage patterns are not dealt with in detail.

Computers are commonly the single biggest source of energy use, and as such, contribute significantly to internal heat gains [8,9]. Moorfield et al. conducted a monitoring study of small power use in 25 offices in California over a 2-week period [15]. Power demand data for 470 plug load devices was collected at 1-min intervals through the use of plug monitors and the data were extrapolated based on an inventory of nearly 7000 devices. Results revealed that computers and screens were responsible for 66% of small power consumption in offices.

Significant improvements in the energy efficiencies of computers have been observed in the last few decades, resulting in reduced energy requirements [16]. This can be attributed in part to initiatives such as Energy Star, an international certification scheme for consumer products that defines performance criteria including maximum power demand levels at different operating modes [17]. Published data suggests that newer computers require less energy in ‘low power’ modes than older computers [18,19], however, the demand for computers with increased processing power has resulted in higher power demands when the computers are active, as illustrated in Fig. 1 (adapted from [18,19]).

More recently, a review of UK benchmarks for small power consumption against monitoring data for a small sample of in use office equipment revealed similar results, highlighting an increase in power demand in active modes and a further reduction in demand for low power modes [7]. The same study also revealed the challenge of keeping benchmarks up to date with fast paced development of computer technologies. Table 2 provides a summary of key published data regarding energy requirement of both laptops and desktops, highlighting the trends discussed above. Note that figures for laptop computers exclude the power demand for the in-built screens, as laptops are typically connected to a desktop screen when used in an office environment.

As observed in Table 2, laptop computers consume only a fraction of the energy of desktop computers, presenting a big opportunity for energy savings in office buildings [16]. Energy efficiency is a critical issue for laptops as it determines the length of time the machine will be able to run from its battery. As a result, laptops generally have lower power demands whilst also going into low power modes more quickly in order to preserve battery power. The recent proliferation of laptop computers will have a large impact on the

<table>
<thead>
<tr>
<th>Nomenclature</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>u</td>
<td>uncertainty</td>
</tr>
<tr>
<td>t</td>
<td>Student’s t distribution using n – 1 degrees of freedom</td>
</tr>
<tr>
<td>n</td>
<td>the number of samples</td>
</tr>
<tr>
<td>S</td>
<td>standard deviation</td>
</tr>
<tr>
<td>P</td>
<td>power (W)</td>
</tr>
<tr>
<td>T</td>
<td>time of day</td>
</tr>
</tbody>
</table>

Fig. 1. Energy requirements of desktop computers manufactured before and after 2000.
overall energy consumption of office buildings: laptop shipment figures are projected to be triple that of desktops in the next few years [20]. Technological advancements such as the evolution of thin client computers and tablets are likely to drive power demand down even further, with thin clients being widely used in schools already [21]. This technology reduces power demand and resultant heats gains locally by shifting these to centralised processors with higher efficiencies [22].

However, power demand is only one factor affecting the total energy consumption of computers. Arguably, the way in which a computer is used is a more significant factor in determining the total energy consumption of computers [16]. Nonetheless, there is little research into usage patterns and behavioural factors with most of the existing work focusing solely on the split between energy consumed during working hours and out-of hours.

A monitoring study of 5 office buildings by Masoso et al. revealed that more energy was being used out-of-hours (56%) than during working hours (44%), largely due to occupants leaving lighting and equipment on at the end of the day [23]. More recently, a study into the after-hours power status of office equipment highlighted a significant variation amongst the number of computers switched off after hours, ranging from 5% to 67% [24]. Amongst the monitored computers, the rate of after-hours turn off was larger for laptops than desktops. Focusing on daytime usage, a study looking into the energy savings potential of office equipment power management suggested that on average, the monitored computers were powered on for 6.9 h a day, being in active mode for 3 h per day [25].

Studies dating back to the 90s suggest that on average, computers are active for approximately 9% of the year [26]. In a detailed monitoring study of 3 desktop computers, Nordman et al. calculated that computers were active between 17 and 31% of the time during workdays, falling to 9–16% when all days were considered [27]. More recently, Moorefield et al. monitored 61 desktops and 20 laptop computers in-use in 25 offices in California over a two-week period [15]. Results demonstrated that desktops spend on average 30% of the time on active mode, compared to 10% for laptops. Mean monitored time spent off highlights further energy savings potential with laptops spending 26% of the time off compared to 7.2% for desktops.

In addition to usage patterns, power management settings can have a significant impact on the energy consumption of computers; influencing the amount of time a computer spends in different operating modes [2]. Power managed computers are programmed to enter a low power mode after a specified time of inactivity. A study carried out in 2004 revealed that if power management settings were applied to switch a computer to low power mode after 5 min of inactivity, 76% of the idle time would be spent on low power mode [25]. Alternatively, setting the time delay to 60 min resulted in the computer only spending 20% of its idle time in low power mode. A separate study carried out by the Australian National Appliance and Equipment Energy Efficiency Program (NAEEEP) demonstrated that aggressive power management (powering down computers after 5 min of inactivity) resulted in a reduction of annual energy consumption by approximately 75% compared to a scenario when no power management settings were applied [28].

When estimating the peak demand and energy consumption of computers, it is also vital to consider usage diversity [29]. Actual peak demand for computers (and subsequent energy consumption) in a given area of a building will always be less than the sum of power demand for each computer due to usage diversity [30]. Diversity factors need to be applied to load calculations in order to limit oversizing of cooling plant [4]. The diversity factor of computers (or any given equipment) is defined as the ratio of measured heat gains to the sum of the peak gain from all equipment [31]. A study conducted in 1994 measured the diversity factor of 23 areas within 5 office buildings, highlighting a significant variation in diversity, ranging form 37–78% [26]. More recently, Wilkins and Hosni proposed diversity factors for individual office equipment, recommending that factors of 75% and 60% should be applied to computers and screens (respectively) in load calculations [32]. Measured diversity during weekends was observed to be 10% and 30% for computers and screens, respectively.

The past decade has seen a major shift towards flexible working practices in both private and public sectors fuelled by tougher markets and technological advances [33]. The recent proliferation of hot-desking is largely driven by a desire to reduce the cost of physical office space, and is particularly attractive to organisations where employees are regularly ‘on the road’ or working remotely [34]. It effectively increases building utilisation also increasing usage diversity, which is likely to have a significant impact on internal heat gains due to ICT equipment. Research into the

Table 1
ECG 19 benchmarks for small power consumption (i.e. office and catering equipment).

<table>
<thead>
<tr>
<th>Type</th>
<th>Electricity consumption (kWh/m²)</th>
<th>Power load density (W/m²)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Good practice</td>
<td>Typical</td>
</tr>
<tr>
<td>Type 1: Naturally ventilated cellular</td>
<td>14</td>
<td>21</td>
</tr>
<tr>
<td>Type 2: Naturally ventilated open plan</td>
<td>23</td>
<td>32</td>
</tr>
<tr>
<td>Type 3: Air conditioned standard</td>
<td>28</td>
<td>37</td>
</tr>
<tr>
<td>Type 4: Air conditioned prestige</td>
<td>36</td>
<td>47</td>
</tr>
</tbody>
</table>

Table 2
Published energy requirements figures for desktop and laptop computers.

<table>
<thead>
<tr>
<th>Source</th>
<th>Power demand (W)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Desktop computers</td>
</tr>
<tr>
<td></td>
<td>Active</td>
</tr>
<tr>
<td>Wilkins and McGaffin [31]</td>
<td>56</td>
</tr>
<tr>
<td>Nordman et al. [27]</td>
<td>36–55</td>
</tr>
<tr>
<td>Mungwittikul and Mohanty [26]</td>
<td>36–48</td>
</tr>
<tr>
<td>Kawanoito et al. [19]</td>
<td>30–60</td>
</tr>
<tr>
<td>Roberson et al. [18]</td>
<td>70</td>
</tr>
<tr>
<td>Hosni and Beck [41]</td>
<td>50–100</td>
</tr>
<tr>
<td>Moorefield et al. [15]</td>
<td>79</td>
</tr>
<tr>
<td>Menezes et al. [7]</td>
<td>64–169</td>
</tr>
</tbody>
</table>
development of workplaces also suggest that further reliance on ICT is likely to occur regardless of the adoption of flexible working practices [35].

A recent study modelled the impact of two possible future scenarios for computer use in office buildings [36]:

(1) **Energy conscious scenario:** ICT acquisition policy is driven by an effort to minimise energy consumption and carbon emissions.

(2) **Techno explosion:** Maximisation of productivity gives users freedom to select the level of ICT demand they need.

Results suggest that for a building with best practice fabric design, a techno-explosion scenario would result in cooling demands almost double that of the energy conscious scenario, highlighting the potential impact that small power equipment can have on the energy performance of the building and suggesting the need for greater understanding of the likely trends and factors influencing small power consumption.

### 3. Methodology

Two new modelling approaches are presented, the first is base on the sampling of measured data, whereas the second is new “bottom-up” approach that is independent of the need for monitored data.

#### 3.1. Model 1: random sampling of monitored data

The first model developed in this study relies on the random sampling of detailed monitored data to represent an office space with a defined quantity of different types of small power equipment. Daily power demand profiles (in 1-min intervals) were randomly selected from a database of monitored data and aggregated to represent the number of installed equipment. This process was repeated 30 times to assess the variance of the outcomes, providing prediction limits within which estimated power demand is expected to fall. An inherent strength of this approach is that it avoids the need for assumptions regarding the expected usage profiles of individual equipment, relying on the monitored data to account for such variations.

Table 3 provides a summary of the monitored equipment included in the database used to predict power demand profiles and energy consumption. It also includes the number of daily profiles available for each equipment type, as well as their respective quantities within the office space under investigation. The selection of devices included in the monitoring study was based on the installed quantities and expected energy use, also attempting to capture information regarding the expected variability of usage.

With the exception of LCD computer screens, at least 8% of the installed equipment (per type) was monitored. Previous research by the authors suggests low variability of power demand by computer screens resulting in fewer screens being monitored as part of this study.

Monitoring took place over 3 months at 1-min sample rates and equipment with similar specifications was grouped together to increase the sample size (within the given monitoring period length). Class 1 accuracy Telegesis ‘ZigBee Plogg-ZGB’ plug monitors with a published measurement uncertainty of <0.5% were used. According to Lanziser et al., sampling faster than at 1-min intervals does not provide significant benefit and that monitoring periods longer than a few months provides little improvement in estimating annual energy use [37]. By grouping similar equipment used by different users, the sample also provides a wide variety of equipment-user combinations, helping to account for elements of user behaviour in the predictions. The monitored data was split into weekdays and weekends allowing for two sets of profiles to be calculated respectively. No filtering was done to exclude days in which the equipment was not used as the ratio of operational/non-operational days was used to account for usage diversity.

A daily profile for each equipment type was calculated by randomly selecting profiles from the database (for weekdays and weekends separately). For example, a summed profile for the 19 high-end desktop computers was calculated by adding up 19 randomly selected weekday profiles out of the 78 available in the database. This process was repeated 30 times in order to assess the variability of the data, allowing for 95% prediction limits to be calculated using Eq. [1] as follows:

\[
    u = \bar{x} \pm t \cdot S \sqrt{\frac{1}{n} + 1}
\]

where \( u \) is the uncertainty, \( t \) is Student’s \( t \) distribution using \( n - 1 \) degrees of freedom, \( n \) is the number of samples and \( S \) is the standard deviation.

Daily profiles were calculated in this manner for each equipment type, resulting in a total power demand profile for weekdays and weekends alongside their prediction limits. Daily energy consumption predictions were calculated based on the daily profiles for weekdays and weekends, also including upper and lower prediction limits. The data was then extrapolated to monthly consumption by assuming 20 weekdays and 8 weekend days per month, whilst annual consumption was based on 52 weeks (each with 5 weekdays and 2 weekend days).

#### 3.2. Model 2: bottom-up model

The second model takes the form of a simple bottom-up approach, inspired by the methodology set out in CIBSE Guide F and TM54, addressing the needs of designers and the wider industry more closely. It is informed by findings from the development of Model 1 but does not rely directly on detailed monitored data. The model also allows designers to assess the impact of different variables on the outputs, encouraging informed discussions with the prospective occupier.

The model requires input data relating to the equipment used, the building, equipment operation and usage patterns.

#### 3.2.1. Equipment inputs

The first set of inputs relate to the types of equipment procured or installed in the area under investigation. These are split under the following categories: computers, screens, printers/copiers, catering and other. Quantities for each equipment type are provided as absolute values and the model calculates the percentage each equipment type represents for each category.

The power demand of each piece of equipment is characterised into three operational modes: ‘off’, ‘low’ and ‘on’.

- \( P_{\text{off}} \) is the lowest power draw whilst the equipment is connected to the mains.
- \( P_{\text{low}} \) is defined as a low power mode that the computer is capable of entering automatically after a period of inactivity (also commonly referred to as stand-by).
- \( P_{\text{on}} \) encompasses all the difference operational modes whilst the machine is on but not ‘asleep’ (including idle and active states).

According to Wilkins and Hossni, two modes of operation (active and low) are appropriate for the purpose of load calculations [32]. The addition of the ‘off’ mode allows for further insight into the impact of out-of-hours usage. Although power demand can vary significantly whilst the machine is active, the widely established Energy Star framework proposes that computers spend the greater
Table 3
Equipment in the database and installed quantities in the office space under investigation.

<table>
<thead>
<tr>
<th>Equipment type</th>
<th>Database</th>
<th>Quantity of installed equipment</th>
<th>Weekday profiles</th>
<th>Weekend profiles</th>
<th>Quantity of installed equipment</th>
<th>Percentage of installed equipment monitored</th>
</tr>
</thead>
<tbody>
<tr>
<td>Laptop computer</td>
<td>8</td>
<td>512</td>
<td>240</td>
<td>99</td>
<td>8.1%</td>
<td></td>
</tr>
<tr>
<td>High-end desktop computer</td>
<td>3</td>
<td>180</td>
<td>78</td>
<td>19</td>
<td>15.8%</td>
<td></td>
</tr>
<tr>
<td>Low-end desktop computer</td>
<td>2</td>
<td>120</td>
<td>52</td>
<td>22</td>
<td>9.1%</td>
<td></td>
</tr>
<tr>
<td>19” LCD screen</td>
<td>1</td>
<td>120</td>
<td>26</td>
<td>22</td>
<td>1.4%</td>
<td></td>
</tr>
<tr>
<td>21” LCD screen</td>
<td>1</td>
<td>60</td>
<td>26</td>
<td>4</td>
<td>4.5%</td>
<td></td>
</tr>
<tr>
<td>Large photocopier</td>
<td>1</td>
<td>60</td>
<td>26</td>
<td>4</td>
<td>25%</td>
<td></td>
</tr>
<tr>
<td>Plotter</td>
<td>1</td>
<td>60</td>
<td>26</td>
<td>1</td>
<td>100%</td>
<td></td>
</tr>
<tr>
<td>Coffee machine</td>
<td>2</td>
<td>40</td>
<td>16</td>
<td>2</td>
<td>100%</td>
<td></td>
</tr>
<tr>
<td>Fridge</td>
<td>1</td>
<td>20</td>
<td>8</td>
<td>2</td>
<td>50%</td>
<td></td>
</tr>
</tbody>
</table>

proportion of time on idle whilst operational [17]. As such, idle demand values can be used to adequately represent the ‘on’ mode input.

Power demand values can be obtained from published benchmarks or if the machines being specified are Energy Star rated, these can be obtained from their database available online [38]. In the case of refurbishments or when the appliances being installed are readily available, these can be monitored for short periods of time to inform better inputs. Plug-in devices with an internal display such as the ‘Eergy energy monitoring socket’ (with accuracy within 2%) are widely available and can provide live readings of power demand [39].

The model provides four usage profiles to be assigned to each type of computer and screen controlled by individual users (as a percentage of the total number of equipment installed):

- transient – users who are often out of the office or away from their desks;
- strict hours – users who work strictly during the company’s standard working hours and who are at their desks for the majority of the working day;
- extended hours – users who often arrive earlier or leave later than the company’s standard working hours and who are at their desks for the majority of the working day;
- always on – users who are required to leave their machine on all the time.

These profiles were established as part of previous work by the corresponding author [40] based on an analysis of the detailed monitoring data for different users, and allows for different usage patterns to be accounted for. This is of particular relevance when considering different workplaces, for example: a call centre is likely to have a high percentage of strict hour users whereas a law firm might have a higher percentage of transient users. An analysis of the time-series demand profiles by different users demonstrated varying hours of operation by different computers, yet these were observed to be fairly consistent for individual users. It is anticipated that the proportion of usage profiles can be established based on detailed discussions with the client and/or prospective occupier.

Usage profiles must also be assigned to ‘communal’ equipment such as printers and photocopiers as well as catering appliances. If the four profiles are deemed to be an inappropriate representation of the usage of these appliances, more representative profiles can be developed manually and applied instead.

Table 3 details the equipment inputs used to characterise the office space under investigation based on a walkthrough audit of the installed equipment alongside findings from the monitoring study used to develop Model 1.

3.2.2. Operational inputs

Inputs regarding the operational characteristics of the office include:

- $T_{arr(norm)}$ = standard arrival time;
- $T_{dep(norm)}$ = standard departure times
- $T_{arr(ext)}$ = extended arrival time;
- $T_{dep(ext)}$ = extended departure times.

The model also requires an estimate of the proportion of equipment switched off at the end of the day (excluding those who are assigned an ‘always on’ profile) and expected usage diversity (on weekdays and weekends). The model also requires information on whether reduced occupancy is expected during lunchtime and if so, when this is likely to occur. Table 4 illustrates the operational inputs used to characterise the office space under investigation.

Table 4
Equipment inputs for Model 2.

<table>
<thead>
<tr>
<th>Equipment type</th>
<th>Quantities</th>
<th>Power draw (W)</th>
<th>Usage profiles (%) time</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Absolute</td>
<td>Off Low active On (average)</td>
<td>Transient Strict hours Extended hours Always On</td>
</tr>
<tr>
<td>Computers</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>High-end desktops</td>
<td>19</td>
<td>14% 1 80 150</td>
<td>15% 30% 30% 25%</td>
</tr>
<tr>
<td>Low-end desktops</td>
<td>22</td>
<td>16% 1 30 40</td>
<td>10% 70% 10% 10%</td>
</tr>
<tr>
<td>Laptops</td>
<td>99</td>
<td>71% 1 20 30</td>
<td>30% 30% 40% 0%</td>
</tr>
<tr>
<td>Screens</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>19” LCD screen</td>
<td>128</td>
<td>85% 0 1 25</td>
<td>20% 50% 30% 0%</td>
</tr>
<tr>
<td>21” LCD screen</td>
<td>22</td>
<td>15% 0 1 45</td>
<td>20% 50% 30% 0%</td>
</tr>
<tr>
<td>Printers and copiers</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Photocopier</td>
<td>4</td>
<td>80% 30 30 220</td>
<td>0% 0% 100% 0%</td>
</tr>
<tr>
<td>Plotter</td>
<td>1</td>
<td>20% 120 120 170</td>
<td>0% 0% 100% 0%</td>
</tr>
<tr>
<td>Catering</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fridge</td>
<td>2</td>
<td>50% 0 100 120</td>
<td>0% 0% 0% 100%</td>
</tr>
<tr>
<td>Coffee Machine</td>
<td>2</td>
<td>50% 25 25 350</td>
<td>0% 0% 0% 100%</td>
</tr>
</tbody>
</table>
Wilkins and Hosni suggest that a diversity factor of 75% should be applied to computers in load calculations, with weekend usage diversity ranging from 10% to 30% [32]. A usage diversity factor of 75% was applied, with a weekend diversity of 15% accounting for occasional weekend workers.

Daily profiles of computer diversity published in Wilkins and Hosni demonstrate that peak diversity can vary on a daily basis, ranging by up to 20% [32]. In order to account for such variations, the model generates two sets of power demand profiles (and subsequent energy consumption figures) by utilising a low-end and high-end usage diversity factor. These are assumed to be 10% lower and higher, respectively, than the diversity factor established in the model inputs, accounting for a total variation of 20% in line with data published by Wilkins and Hosni [32].

3.2.3. Usage profiles

The operational inputs are used to adjust the usage profiles as illustrated in Figs. 2 and 3. $P_{\text{base}}$ represents the base-load and

![Fig. 2. Usage profiles applied to computers in Model 2.](image)

is calculated based on the proportion of equipment switched off, representing a ratio between $P_{\text{off}}$ and $P_{\text{low}}$ accordingly. If lower occupancy levels are expected over lunch, the usage profiles for screens are modified to include a dip between the specified times. Results from Model 1 suggest that the cumulative power demand of screens is likely to reduce by approximately 25% at lunchtime, hence, $P_{\text{lunch}}$ is estimated to be $P_{\text{on}} \times 0.75$. No such drop in power demand was observed in the monitored profiles for computers, hence these are modelled as a constant over lunchtime.

3.2.4. Outputs

The model calculates power demand profiles in kW (and W/m²) for a typical weekday by multiplying the power demand of each item of equipment at different operational modes to the selected usage profiles. The low-end and high-end usage diversity factors (±10% of the diversity factor specified in order to account for daily variability in usage diversity) are applied to the cumulative power demand profile, accounting for daily variations in usage diversity. This approach also accounts for the inherent difficulty in establishing an accurate estimate of diversity factor, especially at the design stage. As such, the model’s outputs are presented as a range (between the high-end and low-end scenarios). Weekend power demand profiles are calculated in a similar way, yet rely on the specified usage diversity factor for weekends. If the office is unoccupied during weekends, the base-load is applied throughout.

![Fig. 3. Usage profiles applied to computer screens in Model 2.](image)

Fig. 4 illustrates the power demand profiles calculated by the model. This includes low-end and high-end outputs for weekdays and weekends. Energy consumption values are calculated based on the summed energy consumption of typical weekday and weekend power demand profiles. Monthly consumption is based on 20 weekdays and 8 weekends, whilst annual consumption is based on 52 weeks (each with 5 weekdays and 2 weekends).

4. Results

4.1. Model 1: comparison against metered data

Fig. 5 illustrates the low-end and high-end predictions alongside metered power demand profiles for the office space under investigation over five different weekdays. Although the predicted profiles are in 1-min intervals, metered data is illustrated in 15-min intervals, as that is the highest resolution available with the automatic metre reading (AMR) system. The metered profiles fall within the predicted range before 8 am and after 8 pm (i.e. base load), often being at the higher end of the prediction range. During the working hours the metered demand is observed to be constantly around the high-end prediction, which is observed to underestimate the demand on occasion, especially around lunchtime. It is likely that the discrepancy in the data resolution (i.e. 1-min interval prediction vs. 15-min interval metered demand for comparison) could be partly to blame for some of the instances when the metered profiles fall below the high end prediction, as higher averages over a 15-min period can be expected as a result of the frequent oscillation in the
predicted power demand. The presence of plug loads not included in the model (such as mobile phone chargers, desk fans and task lighting, etc.) may also be to blame for the underestimation of power demand. The predicted profiles correlate well to the metered data during the transition between the base load and peak demand (and vice versa), including a dip around lunchtime which is also observed in the metered data. The graph also includes the profile used in cooling demand calculations for compliance with Building Regulations in England and Wales in line with the National Calculation Methodology (NCM). In this case, the NCM profile would slightly overestimate the operational demand when the office is occupied, especially around the beginning and end of the working day, whilst significantly underestimating overnight heat gains.

Fig. 6 compares the predicted range of monthly energy consumption against metered data for 9 months in 2012 (metering failures prevented further months from being included). Metered monthly data was normalised by accounting for 28 days (on a pro-rata basis). Results illustrate that metered consumption falls within the predicted range for all months. Similarly to the power demand analysis, most of the metered data fall in the higher end of prediction range (with the exception of December).

Although the results demonstrate a good correlation between predictions and metered energy data, this approach is heavily reliant on detailed monitored data, which is not widely available. Moreover, its ability to predict power demand profiles is directly related to the quantity and quality of the monitored data. Equipment, behaviours and operational characteristics that have not been monitored will not be accounted in the predictions. This limits the applicability of the tool to assess the impact of different variables on the power demand and energy consumption.

4.2. Model 2: comparison against metered data

Fig. 7 illustrates the low-end and high-end predictions alongside metered power demand profiles for the office space under investigation over five different weekdays. A good correlation is observed for peak demand and base-loads, with most of the metered data falling within the predicted range. The model predicts a steeper and slightly earlier rise between the base-load and peak demand in the morning, yet one of the metered profiles lies very close the predicted range. The decrease in power demand at the end of the working day is represented fairly well by the prediction range which only slightly overestimates the time it takes for power levels to descend to the base-load. It is worth noting that predictions are made in 1-h intervals whereas the metered data has a frequency of 15 min. This discrepancy in granularity between both sets of data inherently presents a challenge to the model, yet results are still reasonable.

Fig. 8 compares the predicted range of monthly energy consumption against metered data. Results illustrate that metered consumption falls within the predicted range for all months except for December. This is likely due to fewer working days during the holiday season. In light of these findings, the model has been adjusted so that the ‘low’ prediction represents a typical December month, including 15 working days as opposed to 20 working days.

Although the bottom-up model provides greater flexibility to estimate the power demand and energy consumption of different office buildings, it relies on assumptions of the likely operation of the small power equipment in the office space being modelled, and this may not be known at the design stage. It is likely that such a model would be used in conjunction with published benchmarks, which might not be representative of the specific equipment in use. The model’s reliance on hourly profiles might also result in the cellular data not being suitable for energy consumption modelled.
underestimation of peaks (which can have implications in subsequent predictions of cooling demands).

5. Validation

In order to assess the validity of the outputs from both models, a blind validation was performed in a different office building occupied by the same company. This approach ensured a level of consistency in the types of equipment used and organisational practices, whilst introducing uncertainties regarding the operational characteristics of the office space. At the time at which the models were produced, no metered energy data was available to the researcher. Predictions relied on an inventory of installed equipment and informal conversations with a few of the occupants.

5.1. Validation of Model 1

The validation model relied on the same database of monitoring equipment, yet the quantity of installed equipment was adjusted to represent the new area under investigation. Some of the equipment installed in the office used for the validation was not included in the monitoring database (namely desktop printers, microwaves and a ‘hydroboil’). Out of these, the water heater was deemed to be a significant contributor consisting of a 3 kW heating element which was constantly on between 7 am and 7 pm daily. As such, a constant load of 3 kW was added to the calculated profile between 7 am and 7 pm. Considering the more probabilistic operation of desktop printers and microwaves (as well as smaller expected power demands), no assumptions were made to include these in the model. This highlights the limitations of the approach discussed earlier, whereby an extensive database of monitored data would be required for the wide applicability of the model.

Fig. 9 illustrates the low-end and high-end predictions for the blind validation alongside metered power demand profiles for the office space over five different weekdays. Similarly to the original example, the metered profiles fall within the predicted range outside working hours and daytime power demand is often at the highest end of the predicted range. In this office space however,
metered power demand increases at lunchtime, probably due to the presence of a small kitchen within the office space. The absence of monitored data for microwave ovens is likely to have limited the model’s ability to predict such peaks, contributing further to the underestimation of power demand during the working day. Previous research by the authors suggests that microwave ovens’ can have a maximum demand in excess of 1.5 kW [7], being a significant source of power demand. The transition between the base-load and peak (and vice versa) is represented very well in the prediction ranges. When compared to the NCM profile, the model results provide a much better prediction of power demand throughout the day. In this particular office space, the NCM profile would significantly overestimate peak demand (by more than 50%) yet still underestimating overnight night gains.

Fig. 10 compares the predicted range of monthly energy consumption against monthly metered data for 8 months leading up to the validation exercise (normalised for 28 days). Results illustrate that metered consumption falls within the predicted range for all months.

5.2. Validation of Model 2

For the validation model, power draw values and usage profiles were consistent with those used in the original example, following the assumption that similar operational characteristics would be observed in offices occupied by the same organisation. A usage diversity factor of 70% was applied as lower usage was expected in the validation office compared to the original worked example (which was the organisation’s headquarters).

Fig. 11 illustrates the low-end and high-end predictions for the blind validation alongside metered power demand profiles for the office space over five different weekdays. A good correlation is observed for peak demand and base-loads, with few instances where metered peak demand exceeds the prediction range. Once again lunchtime demand is underestimated and this could be addressed by establishing catering-specific usage profiles. The transition between the base-load and peak (and vice versa) are represented well in the prediction range, except for a slower decrease in power demand late at night (after 8 pm).

Fig. 12 compares the predicted range of monthly energy consumption against metered data. Results illustrate that metered consumption falls within the estimated range for all months. Note that the low-end prediction now accounts for a typical December month by including only 3 working weeks (i.e. 15 working days and 13 ‘weekends’).

6. Discussion

Both models were observed to provide representative predictions of power demand, yet Model 1 provides estimates with greater granularity, better accounting for the variability in peaks throughout the day. This can be of particular use if the profile

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**Fig. 10.** Predictions and metered monthly energy consumption for the validation of Model 1.

**Fig. 11.** Predictions and metered weekday power demand profiles for the validation of Model 2.

**Fig. 12.** Predictions and metered monthly energy consumption for the validation of Model 2.
generated is used in a DSM to predict cooling demands in buildings that are very sensitive to changes in internal heat gains. Meanwhile, estimates of daily profiles using Model 2 (in 1-h intervals) were still observed to be representative of metered data in intervals as small as 15-min. Although the model based on random sampling of monitored data (Model 1) minimises the need for assumptions regarding the usage patterns of equipment, it also requires significantly more data than the bottom-up model, much of which is not available at the design stage. Alternatively, the bottom-up approach (Model 2) provides a more usable tool with no detriment to the quality of predictions for energy consumption.

Fig. 13 provides a comparison between the results from both models, metered data and benchmarks published in ECG19 (for annual energy consumption and peak power demand) previously referred to in Section 2. The estimates are presented as ranges, in line with the low-end and high-end predictions. Metered data for energy consumption was extrapolated from monthly consumption figures, and power demand ranges represent variations in peak demand throughout the five daily profiles used previously in this study. The benchmark ranges relate to typical and good practice values for Type 3 office buildings, as both offices modelled as part of this study would fall under this category (i.e. air-conditioned standard office). For contextual reference, a wider range including benchmarks for all office types included in ECG 19 are also illustrated in the graph. Model results and metered data are presented for both offices investigated in this study: the original worked example and the validation model.

The ECG 19 range for Type 3 offices would underestimate the annual energy use for the example building and overestimate the consumption in the office used for the validation exercise. Results from both models presented here provide more representative estimates than the benchmarks. When considering the wider range of benchmarks (for all building types), both modelled offices are observed to fall within the given range. When considering peak power demand, the benchmarks are observed to be too high for both modelled offices, with the validation office falling below even the wider benchmark range.

These results highlight the risks associated with the use of high-level benchmarks. Even though the wider range of energy consumption benchmarks encompasses the predicted and measured consumption in both offices, the use of such an extensive range would present a large uncertainty. There is clearly a variation in energy consumption and power demand amongst buildings that would fall under the same benchmark category, suggesting a need for more appropriate, small power specific benchmarks categories or the use of a model such as proposed here. The use of benchmarks for peak demand would have significant implications on the systems design, potentially resulting in oversized cooling systems.

7. Conclusions

This paper has detailed the development and validation of two models for predicting electricity consumption and power demand profiles for small power equipment. Both models have demonstrated a good correlation between metered data and monthly predictions of energy consumption. Prediction ranges for power demand profiles were also observed to be representative of metered data with minor exceptions. Model 1 provides a more robust methodology for predicting the variability in power demand throughout a given day, being of particular use to building services design that are very sensitive to changes in internal heat gains. However, appropriate monitored data for individual appliances must be acquired to suitably represent the office space under investigation, and these might not be available at the design stage.

Model 2 provides representative predictions through a bottom-up approach, relying on data that is commonly available to designers coupled with assumptions regarding the likely usage patterns of the office space. This approach emphasizes the need for a strong dialogue between designers and clients/occupiers, allowing for equipment specifications and operational characteristics to be accurately represented in the model. The modelling tool also facilitates this dialogue, enabling a clear visualisation of the impact of changing certain variables on the overall energy consumption and power demand.

Currently, small power consumption and demand are often estimated based on the use of benchmarks. This approach has its limitations, mostly due to the variability of small power as an end-use, which might not be directly related to current benchmark classifications (i.e. office types). Both models were observed to provide significantly better estimates than ECG 19 benchmarks, which are widely used in the UK. If designers were to utilise either of the models proposed in this study, more representative estimates of small power consumption and demand could be established at the design stage. This would present a significant improvement to predictions of building performance, not only from an energy consumption perspective but also from a thermal comfort standpoint, by ensuring that internal heat gains due to small power equipment are accurately accounted for in the design of building systems.

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