Improving Predictions of Operational Energy Performance Through Better Estimates of Small Power Consumption

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IMPROVING PREDICTIONS OF OPERATIONAL ENERGY PERFORMANCE THROUGH BETTER ESTIMATES OF SMALL POWER CONSUMPTION

By
Anna Carolina Kossmann de Menezes

A dissertation thesis submitted in partial fulfilment of the requirements for the award of the degree Doctor of Engineering (EngD), at Loughborough University

November 2013

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ABSTRACT

This Engineering Doctorate aims to understand the factors that generate variability in small power consumption in commercial office buildings in order to generate more representative, building specific estimates of energy consumption. Current energy modelling practices in England are heavily focussed on simplified calculations for compliance with Building Regulations, which exclude numerous sources of energy use such as small power. When considered, estimates of small power consumption are often based on historic benchmarks, which fail to capture the significant variability of this end-use, as well as the dynamic nature of office environments.

Six interrelated studies are presented in this thesis resulting in three contributions to existing theory and practice. The first contribution consists of new monitored data of energy consumption and power demand profiles for individual small power equipment in use in contemporary office buildings. These were used to inform a critical review of existing benchmarks widely used by designers in the UK. In addition, monthly and annual small power consumption data for different tenants occupying similar buildings demonstrated variations of up to 73%. The second contribution consists of a cross-disciplinary investigation into the factors influencing small power consumption. A study based on the Theory of Planned Behaviour demonstrated that perceived behavioural control may account for 17% of the variation in electricity use by different tenants. A subsequent monitoring study at the equipment level identified that user attitudes and actions may have a greater impact on variations in energy consumption than job requirements or computer specification alone. The third contribution consists of two predictive models for estimating small power demand and energy consumption in office buildings. Outputs from both models were validated and demonstrated a good correlation between predictions and monitored data. This research also led to the development and publication of industry guidance on how to estimate operational energy use at the design stage.

KEY WORDS

Buildings; Performance gap; Energy performance; Operational performance; Predictions; Offices; Small power; Plug loads; Appliances; Electricity consumption; Occupant behaviour.

ACRONYMS / ABBREVIATIONS

AHU	Air Handling Unit
AMR	Automatic Meter Reading
ASHRAE	American Society of Heating and Air-conditioning Engineers
BCO	British Council for Offices
BP	Best Practice (benchmark)
BRE	Building Research Establishment
BRECSU	Building Research Energy Conservation Support Unit
BSRIA	Building Services Research and Information Association
BUS	Building Use Studies
CIBSE	Chartered Institution of Building Services Engineers
CICE	Centre for Innovative and Collaborative Construction Engineering
DCLG	Department for Communities and Local Government
DEC	Display Energy Certificate
ECG	Energy Consumption Guide
EngD	Engineering Doctorate
EPBD	Energy Performance of Buildings Directive
EPC	Energy Performance Certificate
FCU	Fan Coil Unit
GLA	Greater London Authority
GSL	Government Soft Landing
HVAC	Heating, Ventilation and Air Conditioning
NABERS	National Australian Built Environment Rating System
NCM	National Calculation Methodology
POE	Post-Occupancy Evaluation
PROBE	Post-occupancy Review Of Building and their Engineering
RIBA	Royal Institute of British Architects
SBEM	Simplified Energy Model
TM	Technical Memorandum
TSB	Technology Strategy Board
TPB	Theory of Planned Behaviour
TYP	Typical (benchmark)

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LIST OF PUBLICATIONS

The following publications have been produced in partial fulfilment of the award requirements of the Engineering Doctorate during the course of the research. The first five publications are included in the Appendices of this thesis.

PUBLICATION 1 – CONFERENCE PAPER (APPENDIX A)

Menezes, A., Cripps, A., Bouchlaghem, D., Buswell, R. A., 2011. *Analysis of Electricity Consumption for Lighting and Small Power in Office Buildings*. CIBSE Technical Symposium, DeMontfort University, Leicester UK, 6th - 7th September.

PUBLICATION 2 – JOURNAL PAPER (APPENDIX B)

Menezes, A., Cripps, A., Bouchlaghem, D., Buswell, R. A., 2012. Predicted vs. actual energy performance of non-domestic buildings: Using post-occupancy evaluation data to reduce the performance gap. *Applied Energy*, Vol. 97, pp. 355–364.

PUBLICATION 3 – JOURNAL PAPER (0)

Menezes, A., Cripps, A., Buswell, R. A., Bouchlaghem, D., 2013. Benchmarking small power energy consumption in office buildings in the United Kingdom: A review of data published in CIBSE Guide F. *Building Services Engineering Research & Technology,* vol.34, no. 1, pp. 73-86.

PUBLICATION 4 – CONFERENCE PAPER (0)

Menezes, A., Tetlow, R., Beaman, C., Cripps, A., Bouchlaghem, D., Buswell, R. A., 2012. Assessing the impact of occupant behaviour on the electricity consumption for lighting and small power in office buildings. *7th International Conference on Innovation in Architecture, Engineering and Construction*. 15-17 August, The Brazilian British Centre, Sao Paulo, Brazil.

PUBLICATION 5 [UNDER REVIEW] – JOURNAL PAPER (APPENDIX E)

Menezes, A., Buswell, R. A., Cripps, A., Bouchlaghem, D. and Wright, J., 2013. Estimating the energy consumption and power demand of small power equipment in office buildings. *Energy and Building.* [Manuscript under review].

PUBLICATION 6 – INDUSTRY GUIDANCE

CIBSE, 2013. *TM54: Evaluating Operational Energy Use at the Design Stage.* London: Chartered Institution of Building Services Engineers.

PUBLICATION 7 – CONFERENCE PAPER

Menezes, A., Cripps, A., Bouchlaghem, D. and Buswell, R. A., 2011. *Predicted vs. Actual Energy Performance of Non-Domestic Buildings.* Proceedings of the Third International Conference on Applied Energy - Perugia, Italy, pp 1225-1240.

PUBLICATION 8 – CONFERENCE PAPER

Menezes, A., Nkonge, N., Cripps, A., Buswell, R.A. and Bouchlaghem, D., 2012. *Review of benchmarks for small power consumption in office buildings*. CIBSE ASHRAE Technical Symposium, 18-19 April, Imperial College, London, UK

PUBLICATION 9 – INDUSTRY ARTICLE

Menezes, A., 2011. Bridging the gap between predicted and actual energy consumption in non-domestic buildings. *Innovation & Research Focus,* no. 87. [Online]. Available from: http://www.innovationandresearchfocus.org.uk/articles/html/issue_87/energy_consumption_in_non_domestic_buildings.asp [accessed on: 06/06/2013].

PUBLICATION 10 – INDUSTRY ARTICLE

Menezes, A., and Tetlow, R., 2013. *People Power*. CIBSE Journal - September issue, 2013. London: Chartered Institution of Building Services Engineers.

1 INTRODUCTION

The Engineering Doctorate (EngD) programme is a four-year research degree part-funded by the Engineering and Physical Sciences Research Council (ESPRC) and is awarded for research conducted within an industrial context. The work included in this thesis was managed by the Centre for Innovative and Collaborative Construction Engineering (CICE) at Loughborough University and sponsored by AECOM, a global multidisciplinary engineering consultancy.

1.1 RESEARCH CONTEXT

In 2008, the UK Government committed to an 80% reduction in CO_2 emissions, compared to a 1990 baseline (Climate Change Act, 2008). With buildings accounting for approximately 40% of the UK's total carbon emissions, the construction industry is facing increased pressure to deliver energy efficient, low carbon buildings (DTI, 2005). Building Regulations have become increasingly stringent over the last few decades demanding higher levels of energy efficiency, yet most requirements rely on design stage calculations, not on operational performance. There is significant evidence to suggest that the operational energy use in buildings is typically far higher than anticipated (Cohen et al., 1999; Bordass et al., 2001; Bordass et al., 2004; Pegg, 2007; Carbon Trust, 2011; Burman et al., 2012). Meanwhile, operational energy performance is rarely considered at the design stage, with focus being mainly on simplified models for compliance with Building Regulations (Kimpian & Chisholm, 2012; CIBSE, 2013).

If reductions in CO_2 emissions are to be experienced in practice, design stage predictions must be improved to better represent the operation of buildings. As a result design will better match reality, and improvements will be delivered more effectively. This is the main premise behind this EngD which aims to improve predictions of operational energy use through better estimates of small power consumption in commercial buildings. As an energy end-use, small power encompasses office equipment such as computers, screens and printers, catering equipment such as vending machines and microwaves, as well as other miscellaneous plug loads. In the USA, small power equipment is estimated to consume approximately 20% of the country's primary energy use and this is expected to increase in the next 20 years (USDOE, 2009). Similar levels of energy use associated with small power are found in the UK, yet these loads are not under the remit of Building Regulations (often being referred to as unregulated loads). As such, detailed estimates of small power consumption are rarely undertaken, and designers often rely on industry benchmarks, inherently failing to account for the variability of small power loads in different buildings.

1.2 RESEARCH SCOPE

At the outset of this work, the researcher was given a preliminary brief to investigate the discrepancies between the predicted and in-use energy performance of commercial buildings. This brief encompassed an array of issues, which were initially investigated through a literature review. Figure 1-1 provides an overview of how the scope was ultimately focused. Upon reviewing the relevant literature, it was evident that the exclusion of numerous sources of energy use from compliance calculations was a key factor contributing to discrepancies between design estimates and operational performance. Supporting this, preliminary findings from the research project revealed that small power loads were not only a sizeable end-use, but also one with significant variations amongst different buildings (even those with similar uses and operational characteristics). Of these loads, computers were the single largest consumer of electricity amongst small power office equipment, hence becoming the ultimate focus of this thesis. The work investigated commercial office buildings, yet findings are more widely applicable to other building types.

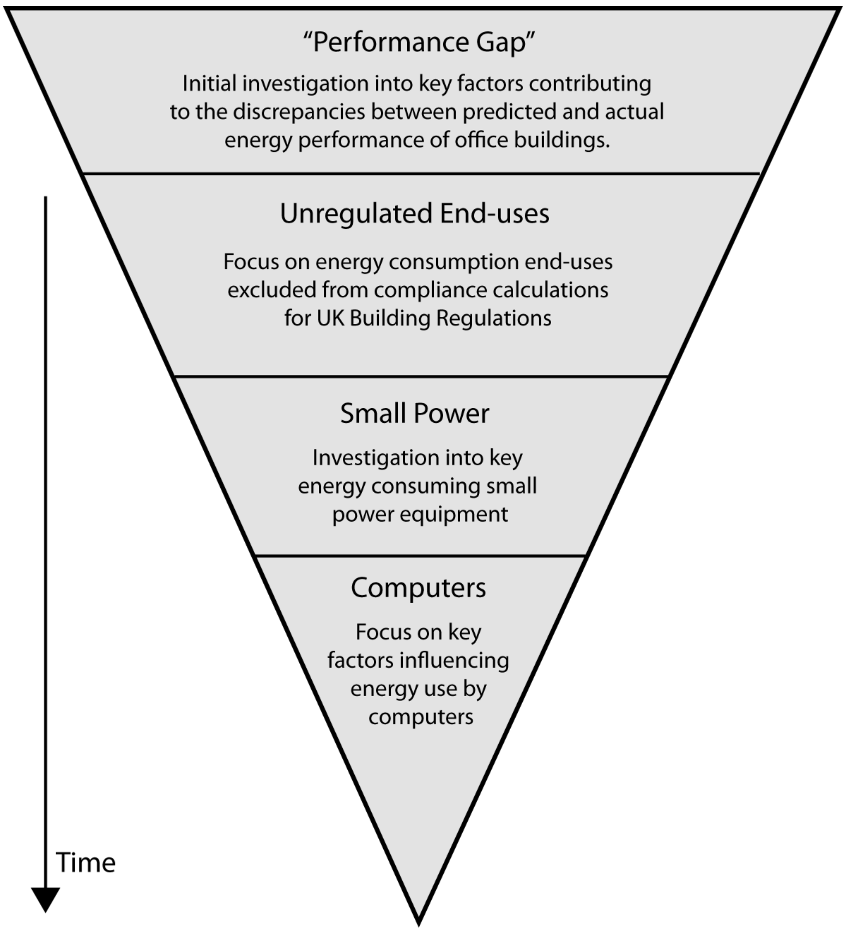

Figure 1-1: Scope of work throughout the research project

Small power equipment can impact the operational energy performance of a building not only by consuming electricity, but also by generating heat, which can in turn increase the building's cooling demand. This thesis focuses on the energy consumption resulting directly from the use of small power equipment but also attempts to address the wider issues surrounding power demand and internal heat gains.

1.3 AIMS AND OBJECTIVES

The aim of this thesis is understand the factors that generate variability in small power consumption in commercial office buildings and to demonstrate how these factors should be accounted for in order to generate more representative, building specific estimates of electricity consumption.

The specific objectives of the research are detailed below:

Objective 1
Investigate the key factors contributing towards the discrepancies between predicted and operational energy performance through a review of existing literature.

Objective 2
Explore the impact and variability of small power consumption on the operational energy performance of office buildings through post-occupancy studies of multiple tenants within similar buildings.

Objective 3
Assess whether industry benchmarks are representative of small power equipment currently being used in office buildings.

Objective 4
Investigate the contributing factors to variations in small power energy consumption in office buildings.

Objective 5
Develop a model to estimate energy consumption of small power equipment, providing associated predictions of power demand profiles.

1.4 RESEARCH JUSTIFICATION

Current practices surrounding energy modelling focus mainly on simplified models required for compliance with Building Regulations. These do not aim to predict operational energy use and deal solely with fixed building services, excluding numerous sources of energy use such as small power, servers, external lighting and vertical transportation. They also exclude variations in occupant density and operational hours. Results from compliance models often generate unrealistic expectations whilst also creating a risk that expected carbon savings might not materialise. Recent efforts such as CarbonBuzz (2013) are aiming to disseminate the shortcomings of current practices. As a result, clients are becoming increasingly aware of the so called ‘performance gap’.

In order to address client speculation into predictions of operational energy use, designers must account for all energy uses within the building, yet many of these are out of their control. The energy consumption and associated internal heat gains due to small power equipment are particularly complex as they can vary significantly, being heavily influenced by the building occupants. Data regarding in-use energy consumption of small power equipment within the context of buildings is often out-of date and incomplete to fully calculate its impact. As such, there is scope to investigate the use of small power equipment in operational office buildings. Moreover, the development of a model to estimate building specific small power energy consumption would be of great use to designers within the sponsor company and the wider industry.

1.5 THESIS STRUCTURE

The remainder of this thesis is organised into four chapters. An overview of each chapter is provided below.

Chapter Two - Literature Review

Chapter two summarises the findings of a literature review acknowledging previous and parallel research efforts. Topics covered include current practices for regulating energy use in England and Wales; operational and predictive elements contributing to the gap in performance; and a detailed review of publications regarding the energy use of small power equipment, and more specifically computers, in office buildings.

Chapter Three - Research Methodology

Chapter three presents the research methodology adopted and specific methods applied. Methodological considerations are discussed and an overview of the chosen approach is reviewed, including a research map of the key processes undertaken throughout the project. Data gathering techniques include walkthrough audits, meter readings and power demand monitoring at sub-circuit and equipment level, as well as a bespoke behavioural survey. Data analysis of energy consumption and power demand data includes time-series profiles, calculations of mean power demand at different operational modes, as well as estimates of prediction limits and uncertainty.

Chapter Four - Research Undertaken

Chapter four describes the research undertaken to meet the aim and objectives of the project. It is divided into six distinctive sub-chapters relating to six individual studies, and refers to the publications produced during the EngD (included in the appendices). The first study investigates the electricity consumption of small power equipment in two multi-tenanted office buildings, addressing Objective 2 and revealing significant variation in energy use. The second study highlights the potential for using knowledge acquired from existing buildings to inform better predictions of small power energy use, demonstrating that reliable estimates can be obtained by using realistic assumptions. The third study addresses Objective 3, reviewing existing benchmarks for small power consumption in buildings. The fourth study assesses the impact of occupant behaviour on the variations in small power consumption, partially addressing Objective 4. The fifth study provides a detailed evaluation of the contributing factors to variation in energy consumption and usage profiles of computers, further addressing Objective 4. Finally, the sixth sub-chapter details the development and validation of two models for estimating power demand and energy consumption of small power equipment, addressing the final research objective.

Chapter Five - Findings and Implications

The final chapter summarises the main findings from the research, including the impact of the research within the sponsor company and the implications for the wider industry, including the publication of an industry guidance document on design stage evaulations of operational energy use. Three contributions to theory and practice are claimed as a result of this EngD. These cover (i) detailed monitored data of small power equipment in-use, (ii) a cross-disciplinary investigation into the factors influencing variations in small power consumption; and (iii) two validated models for estimating small power demand and consumption at the design stage. Supporting these contributions, additional recommendations for industry and further work are made and a critical evaluation of the research project is drawn.

2 LITERATURE REVIEW

This chapter addresses Objective 1 of this thesis and provides an overview of the existing literature in three relevant subject areas: (i) regulating energy use in buildings; (ii) the performance gap; and (iii) energy consumption of small power equipment. The chapter starts by reviewing the regulatory practices concerning the energy performance of buildings, portraying the context in which this research project was undertaken. This leads to a review of the causal factors contributing to the discrepancies between predictions and operational performance of buildings. This section addresses the drivers and barriers to design stage predictions and post-occupancy monitoring of energy use, also discussing the role of occupants in the energy performance of buildings. Finally, a review of existing research into the use of small power equipment, and more specifically computers, in office buildings is presented.

2.1 REGULATING ENERGY USE IN BUILDINGS

The energy performance of buildings in England and Wales is regulated by Part L of the Building Regulations - Conservation of Fuel and Power. Since its introduction in 1965, Part L has been revised several times, incrementally tightening the requirements for improved energy efficiency levels.

2.1.1 NATIONAL CALCULATION METHOD

Following the implementation of the European Energy Performance of Buildings Directive (EPBD), the 2006 revision of Part L established a National Calculation Methodology (NCM), providing a single simulation-based calculation route for compliance (DCLG, 2006). For non-domestic buildings, the NCM is implemented through the use of a Simplified Building Energy Model (SBEM). Calculations can be carried either through a non-graphical interface (iSBEM) or through accredited third-party simulation software, aiming to address the functional and volumetric complexities of non-domestic buildings (DCLG, 2008).

As a compliance tool, SBEM relies on standard profiles for occupancy patterns and deals solely with regulated loads (i.e. the energy loads controlled by Building Regulations). These include fixed systems for internal lighting, heating, hot water services, air conditioning and mechanical ventilation (DCLG, 2010a). Unregulated loads such as external lighting, vertical transportation, server rooms and small power (including office and local catering equipment) are not included as sources of energy use in SBEM. The NCM includes a set default values for internal gains resulting from small power equipment and these are used to calculate the heating and cooling demands, yet are not reflected in the electricity use calculations (DCLG, 2010b).

2.1.2 UNREGULATED LOADS

Although unregulated loads fall outside of the remit of Building Regulations, their impact on the operational energy performance of buildings has become of increasing interest. In 2009, DCLG undertook a consultation on policy options to enforce zero-carbon new non-domestic buildings by 2019 (DCLG, 2009). The consultation proposed that an element of unregulated energy should be included in the zero carbon standard, highlighting that unregulated emissions for different building types can vary from 5% to 67% (as a percentage of regulated emissions). According to the consultation document, there is a considerable variation in the use of unregulated energy even within the same building types, suggesting the need for specific unregulated energy allowances for different building uses (within the broader building types). This would require extensive research whilst also resulting in a complex system to implement and enforce (DCLG, 2009).

Although DCLG is not inclined to pursue an approach for including unregulated energy allowances in zero-carbon legislation, a number of local authorities are doing so. The 2011 London Plan (Greater London Authority's planning guidance document) requires the inclusion of unregulated emissions in energy statements for planning applications alongside the identification of measures to minimise unregulated emissions (GLA, 2011).

2.1.3 BUILDING LOG BOOKS AND SUB-METERING

From 2002, Building Regulations included two new requirements relating to the operational energy performance of new buildings and major refurbishments: the production of a Building Log Book; and sub-metering of at least 90% of all fuel types (DCLG, 2002).

The building log book should include details of the installed building services and controls, their method of operation and maintenance as well as the metering, monitoring and targeting strategy, including up-to-date records of annual energy use in the building (DCLG, 2002). The Chartered Institution of Building Services Engineer (CIBSE) provides guidance on how to produce a log book in its Technical Memorandum (TM) 31, highlighting the log book's role as a key source of information regarding building energy use (CIBSE, 2006b). According to Jones and Davies (2003), the log book has the potential to promote the efficient operation of buildings whilst also allowing for valuable information to be fed-back to the designers. Yet, according to results from a survey by Liddiard et al. (2008) only 52% of facilities managers and operators are actually using building log books and less than 25% of their clients are stipulating their provision.

The implementation of sub-metering requirements has demonstrated similar shortcomings with poor compliance levels and extensive evidence that many installed sub-metering and monitoring systems have failed to meet expectations (Jones, 2012). Although guidance is widely available on how to develop and implement sub-metering strategies (Carbon Trust, 2007; CIBSE, 2009; BBP, 2011), examples of poor implementation are abundant (Jones, 2012). Key issues include the specification of appropriately sized sub-meters, accurate installation and commissioning, adequate labelling, and identifying a strategy that will provide useful information to improve energy performance. Jones (2008) also highlights the difficulties in sub-metering individual end-uses, emphasising that there are often practical limitations in separately measuring lighting and small power.

2.1.4 ENERGY CERTIFICATION

The implementation of the EPBD resulted in two additional regulatory requirements: Energy Performance Certificates (EPCs) and Display Energy Certificates (DECs).

An EPC must be produced for all new buildings as well as those let or sold. It is based on the calculated CO_2 emissions (in $kgCO_2/m^2$ per year) for the building compared to a notional design to produce an Asset Rating. Similarly to compliance calculations for Building Regulations, EPCs are produced using SBEM and account only for the regulated loads whilst also relying on standard profiles for occupancy hours and patterns. The resultant certificate displays the rating on a scale from A (very efficient) to G (very inefficient) providing a record of the building's asset (not an estimate of their expected energy consumption or carbon emissions).

A DEC must be produced for all non-domestic buildings with a useful floor area greater than 1,000m^2 occupied by a public authority or an institution providing a public service, being frequently visited by members of the public. Unlike an EPC, the DEC displays the operational rating of the building, being based on the actual energy consumption over the preceding year. DECs must be renewed every year, and the previous three ratings must also be displayed on the certificate (where applicable). The operational rating is displayed on a scale from A to G calculated based on comparison against statutory energy benchmarks for the given building type. A DEC must also be clearly displayed in a public area of the building and accompanied by an advisory report listing cost-effective measures to improve its rating.

Despite sharing the same rating scale, EPCs and DECs bear no correlation and are not comparable. Nonetheless, such comparisons are commonly drawn and typically raise the concern that a favourable asset rating does not always materialised in practice. Burman et al. (2012) provide a clear example of this by analysing the performance shortfalls of an academy in North-west England with an asset rating of B and an operational rating of G. Such disparities can cause misaligned expectations to clients and occupiers who are often unable to understand the distinction between both certification schemes. In an analysis of 126 commercial buildings in London, Hogg and Botten (2012) demonstrated that there is little or no correlation between EPC ratings and actual energy performance. Results from the study are illustrated in Figure 2-1 and highlight that the average energy consumption per m^2 of the monitored buildings are remarkably similar regardless of whether the building has an EPC rating of C, D or E. The study also demonstrated significant variability in energy intensity within each EPC rating band.

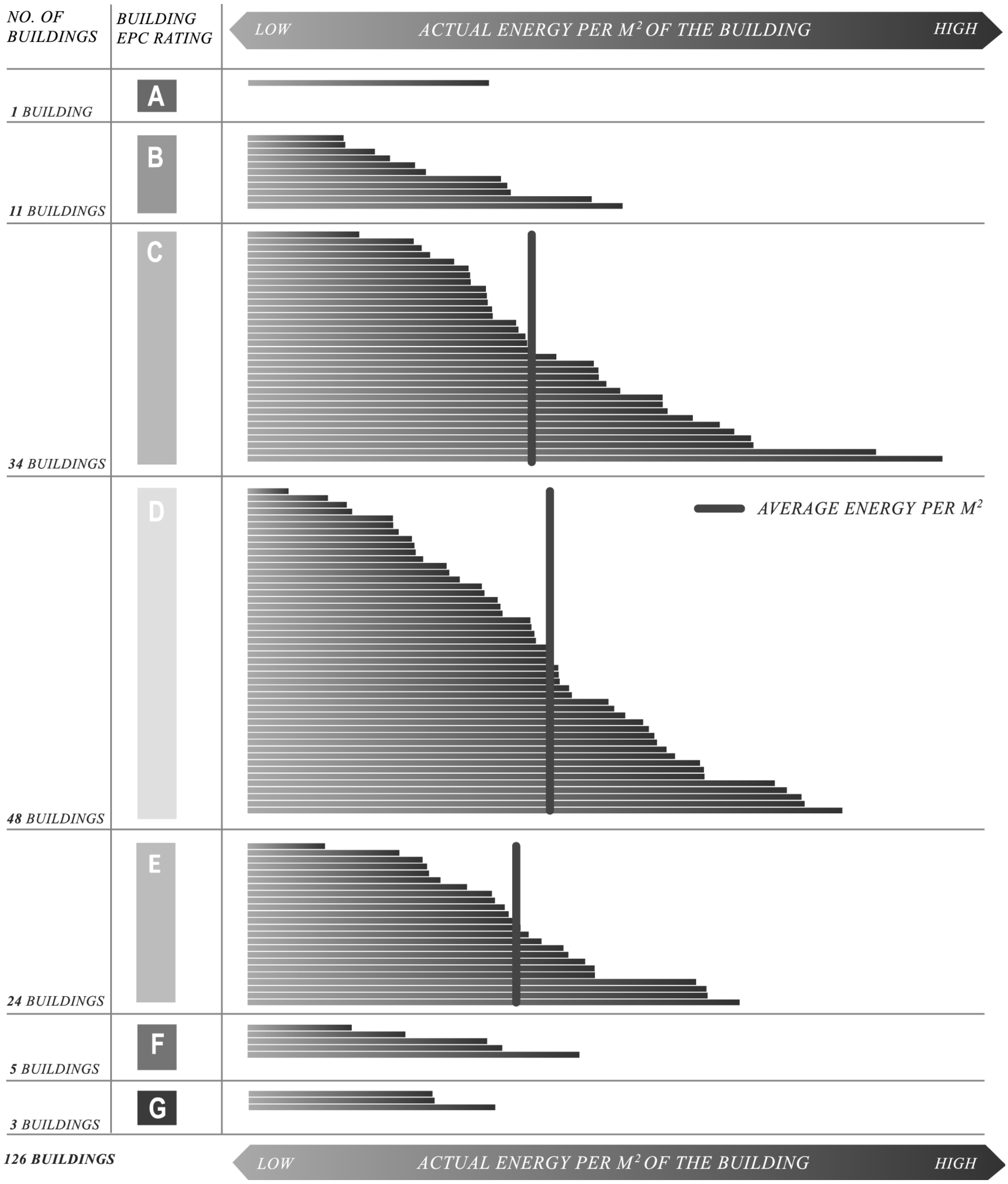

Figure 2-1: Actual energy use of 126 office buildings grouped by their EPC rating

2.1.5 BENCHMARKS

The implementation of DECs resulted in the need for statutory building energy benchmarks, published in CIBSE TM46 (CIBSE, 2008). These are divided into 29 categories representing major building types and provide benchmarks for electricity and fossil thermal energy separately (in kWh/m^2). In 2011, CIBSE commissioned a review of TM46 benchmarks based on DECs lodged since 2008 (Bruhns et al., 2011). Results suggested a good correlation between the benchmarks and actual operational ratings for most categories. The study also revealed that most categories use more electricity and less fossil fuel than the benchmark values, yet these variations can often nullify the differences. According to Bruhns et al. (2011), this reflects the growth in electrical equipment usage in most buildings over recent years, coupled with the internal heat gains these create, as well as improvements in insulation, boilers and heating controls, all of which have combined to reduce heating demand.

CIBSE Guide F includes a compilation of building energy benchmarks and is updated periodically reflecting the best available data at the time of publication (CIBSE, 2012). Similarly to TM46, Guide F includes overall building consumption benchmarks, but it also provides additional sub-categories of buildings differentiating between 'good practice' and 'typical' benchmarks. In addition, detailed benchmarks by component and end-use are also provided for a few building types. Many of these were originally published in Energy Consumption Guides (ECGs) including the widely referenced ECG19 (BRECSU, 2000). First published in 1997, this guide provides benchmarks for individual end-uses for four types of office buildings: cellular naturally ventilated (Type 1); open-plan naturally ventilated (Type 2); standard air-conditioned (Type 3); and prestige air-conditioned (Type 4).

2.1.6 REGULATORY LIMITATIONS

Despite the increasing efforts to enforce higher levels of energy performance, the Building Regulations have been heavily criticised, as many question whether they are stringent enough to meet the Government's CO_2 reduction targets (Bell and Lowe, 2000; Olivier, 2001; Adeyeye et al., 2007; Waddell, 2008). Others fear that the Part L focuses too heavily on energy modelling, which is deeply reliant upon assumptions rather than measurements of actual performance (Dabee, 2009, Cooper, 2013). In a review of compliance verification tools, Raslan et al. (2009) raised serious concerns regarding the credibility of the compliance methodology, demonstrating significant variability in the results obtained through the use of different compliance tools. Meanwhile, studies such as Hogg and Botten (2012) demonstrate that asset ratings do not reflect operational performance, highlighting the need for regulations to focus on actual energy consumption rather than just 'design intent'.

In March 2010, DCLG consulted on a proposal for extending DECs to all commercial buildings (DCLG, 2010c). In support of this, the UK Green Building Council (UKGBC) established a task group calling for wider roll-out of DECs. Consultation responses demonstrated great support from the property sector (UKGBC, 2011). Policy makers are currently consulting on the recast of the EPBD, with a proposal to extend the requirement of DECs to public buildings above 500m^2 (DCLG, 2013).

Recent governmental efforts have been greatly steered by the Energy Act (2011), which includes the provision for establishment of the Green Deal. This privately financed funding scheme applies to all domestic and commercial buildings, allowing the bill payers to obtain energy efficient improvements without having to pay for the upfront cost of the retrofit works (DECC, 2010). The programme relies on an overarching 'golden rule' principle that is based on estimates of energy savings, and many fear that operational savings might not materialise (Quartermaine, 2011; Dowson et al., 2012). The Energy Act also stipulates a minimum standard of energy efficiency making it unlawful for private landlords to lease properties with an EPC rating of less than E, after April 2018.

2.2 THE PERFORMANCE GAP

The PROBE (Post-occupancy Review of Buildings and their Engineering) studies investigated the performance of 23 buildings between 1997 and 2002. The study aimed to expose the industry to the idea of feedback, permitting professionals to admit and openly discuss shortcomings in systems and in-use performance (Cohen et al., 1999). Results highlighted that the measured energy consumption of the buildings were typically significantly higher than predicted in the preliminary design stages (often more than twice as much). Such discrepancies between calculated and measured energy use are often referred to as the performance gap. Several studies reveal that shortcomings often transcend energy performance, affecting additional performance indicators such as air quality, acoustics, and thermal comfort (Leaman and Bordass, 2001; Pegg, 2007; Mumovic et al., 2009; Dasgupta et al., 2012).

Fuelled by increasing evidence surrounding the performance gap, the Royal Institute of British Architects (RIBA) and CIBSE launched CarbonBuzz, a free online platform allowing practices to share building energy consumption data anonymously (CarbonBuzz, 2013). Figure 2-2 illustrates the calculated and measured electricity consumption value for offices and educational buildings that contain both sources of data in the platform, highlighting that measured consumption is often significantly higher than calculated (Ruyssevelt and Robertson, 2013).

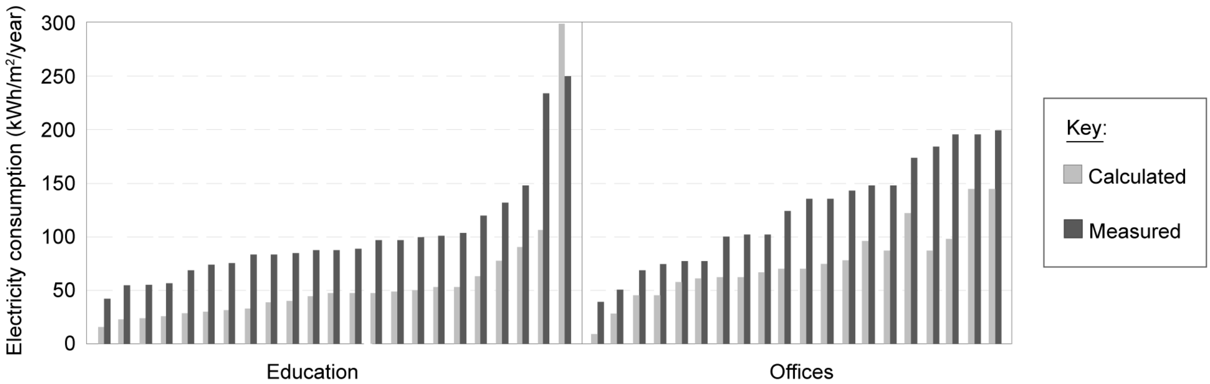

Figure 2-2: CarbonBuzz calculated and measured energy use per sector (adapted from Ruyssevelt and Robertson, 2013)

When comparing calculated performance to measured energy use, it is import to determine the source of calculations. Data contained in the CarbonBuzz platform is often based on results from compliance models, which are often the only calculation performed by designers at the design stage (Kimpian and Chisholm, 2011). Aiming to provide a fairer evaluation, Carbon Trust (2011) compared results from compliance calculations to measured consumption for regulated loads alone. Results from five buildings suggest that regulated consumption can be five times higher than calculated (Carbon Trust, 2011).

According to Bordass et al. (2001) the performance gap is often attributed to a combination of to poor assumptions during design and persistent problems with operation of building services equipment. In other words, current predictions tend to be unrealistically low whilst actual energy performance is usually unnecessarily high. However, the overall problem could be interpreted as an inability of current modelling practices to represent realistic use and operation of buildings in addition to a lack of feedback regarding actual performance.

2.2.1 PREDICTING ENERGY USE

Modelling tools such as SBEM were not developed to calculate operational energy consumption, instead detailed Dynamic Simulation Models (DSMs) can be used to predict the in-use energy performance of a building. DSMs are more suited to the functional and volumetric complexities of non-domestic buildings as they allow for more detailed input options whilst also containing extensive databases for materials and systems (Raslan et al., 2009). Despite these and many other added capabilities, designers often fail to adequately predict energy consumption in buildings (Bordass et al., 2004).

Focusing on the accuracy of energy predictions, there are often two types of errors: internal (problems inherent to the simulation code) and external (introduced by inaccurate assumptions and inputs). Extensive research has been carried out into internal errors, including Judkoff and Neymark (1994), Jensen (1994), Lomas (1996) and DeWit (1997). Although uncertainties are still present, stringent procedures are being implemented to ensure the validity of modelling programs (De Wit, 1995). CIBSE TM33 provides a framework for assessing the validity of commercial software calculation tools, aiming to ensure that dynamic simulation algorithms are technically robust (CIBSE, 2006c). Meanwhile, external errors are more difficult to control and can be heavily influenced by varying user capabilities (Raslan et al., 2009). As DSMs become more complex and flexible, the role of the user becomes increasingly important, yet Bordass et al. (2001) found that designers consistently make poor assumptions when predicting energy use, especially regarding internal heat gains.

According to Bordass et al. (2001), most energy modelling takes little account of true plant and control performance or of occupant and management behaviour. In additional, several end-uses such as control systems, kitchens and computer rooms are often excluded from the models (Bordass et al., 2004). In an investigation of the performance of five academies, Pegg (2007) highlighted that the assumptions used in DSMs were often overly optimistic resulting in significant underestimation of energy consumption. Results from a survey focusing on attitudes, opinions and experiences of UK design engineers revealed that there seems to be little or no consequence for inaccurately predicting building loads and energy consumption (Pegg, 2007).

Initiatives such as the National Australian Built Environment Rating System (NABERS) are encouraging the estimation of operational energy (NABERS, 2011). The methodology emphasises that the building should be modelled as it is expected to operate, and requires that numerous scenarios be considered as part of a risk assessment. Similarly, several US states have adopted the ASHRAE 90.1 standard as their energy code, which includes a building performance rating method accounting for the energy consumption of all end-uses as well as a detailed representation of the HVAC system (ASHRAE, 2004). In the UK however, detailed energy simulations are rare amongst practitioners, with many designers not providing estimations for their buildings (Pegg, 2007). CIBSE is aiming to address this issue by providing guidance to designers on how to evaluate operational energy performance at the design stage (CIBSE, 2013). This Technical Memorandum (TM) was developed by the sponsor company and co-authored by the researcher following the preliminary findings of this EngD. The guide emphasizes the importance of accounting for all end-uses in the building and includes a section dedicated to small power loads. The development of this document highlights the relevance of the research detailed in this thesis and forms part of the contribution of this EngD in a contextual manner.

2.2.2 OPERATIONAL ENERGY PERFORMANCE

In the influential report ‘Rethinking Construction’, Egan (1998) highlighted that ambitious targets alone are not enough to deliver improvement, and that effective measurement of operational performance is essential. This can be achieved through Post-Occupancy Evaluation (POE). In the first RIBA handbook, the final stage of the ‘Plan of Work’ (Stage M) was dedicated to ‘feedback’ and this process was regarded by the institute as the most cost effective way of improving services to future clients (RIBA, 1967). However, in 1972, Stage M was withdrawn from the Architect’s Appointment and POE was no longer regarded as part of an architect’s ‘normal services’ to their clients. According to Cooper (2001), this is likely to have occurred because architects did not receive the appropriate fees for reviewing their projects post-occupancy. Focusing on the issue of cost, Bordass (2003) highlights that the benefits of POE are often spread around numerous stakeholders, so no one party sees themselves as reaping enough benefits to bear the costs incurred. In May 2013, RIBA unveiled its new Plan of Work in which the final Stage (7) in entitled ‘In-use’, with POE being a suggested key support task (RIBA, 2013).

According to Lowe and Oreszczyn (2008), there is a significant lack of information concerning the actual energy performance of our existing building stock (Lowe and Oreszczyn, 2008). A continued absence of such data is likely to lead to a progressive widening of the gap between theory and practice and a failure to achieve strategic goals (Oreszczyn and Lowe, 2010). Aiming to address this issue, the Technology Strategy Board (TSB) has launched the largest POE study since PROBE, investing £8m on performance evaluation studies of recently constructed domestic and non-domestic buildings across the UK (TSB, 2013). The key differential of this project is that applicants will be undertaking the evaluations themselves enabling those who participate in the study to train their own staff and to embed both evaluation practices and the learning process of POE into their organisations. The TSB is taking measures to ensure that all POE data acquired as part of the project be made publicly available via the CarbonBuzz platform.

In 2012, the Government Construction Board launched a Government Soft Landings (GSL) policy (Cabinet Office, 2012). This initiative follows the principles of the BSRIA Soft Landings Framework (BSRIA, 2009), designed to ensure a smooth transition from early design stages to occupations. One of the key elements of both frameworks is the requirement for clear measurements of building performance during the first 3 years post completion. Guidance documents for GSL will be published in 2013 and all Central Government Department projects will have to adhere to the framework by 2016 (Cabinet Office, 2012).

2.2.3 OCCUPANT BEHAVIOUR

According to (Derijcke & Uitzinger, 2006), designing a building in a sustainable manner does not guarantee it will be energy efficient, as consumption is heavily influenced by the behaviour of its occupants. This rationale is one of great significance when investigating both the estimated and operational performances of buildings. In a recent study, Gill et al. (2010) investigated the impact of occupant behaviour on the energy and water consumption of a low-energy housing scheme in East Anglia. The study aimed to quantify the impact of occupant behaviour in the variation of building performance. Results indicated that energy efficient behaviour accounted for 51%, 31% and 11% of the variance in heat, electricity and water consumption, respectively, between dwellings.

Focusing on commercial buildings, Masoso and Grobler (2010) highlighted the impact of poor occupant behaviour during non-occupied hours in office buildings. The work was based on energy audits of 6 buildings and demonstrated that 56% of the energy consumed was used outside working hours. This is largely due to bad occupant behaviour whereby lights and equipment were left on at the end of the day, as well as poor zoning and controls. A further key finding was that 19–28% of the buildings' energy was consumed during the unoccupied part of the weekend.

Despite the substantial evidence that occupant behaviour can significantly impact energy consumption in buildings, there are few studies aimed at quantifying the impact of occupant behaviour on the overall energy consumption of buildings. Gill et al. (2010) attempted such a task through the use of a questionnaire based on the Theory of Planned Behaviour (TPB), highlighting the potential to apply a similar methodology to commercial buildings. The TPB was originally developed by Ajzen (1991) and is arguably the most widely researched behavioural model (Armitage and Conner, 2001). It proposes a model about how human action is guided by attitude, subjective norm and perceived behavioural control. Provided that the behaviour is intentional, TPB predicts the occurrence of a specific behaviour based on the following (Francis et al., 2004):

- whether the person is in favour of doing it ('attitude');
- how much the person feels social pressure to do it ('subjective norm'); and
- whether the person feels in control of the action in question ('perceived behavioural control').

By changing these three 'predictors', the chance that the person will intend to do a desired action can be increased. This concept is illustrated in Figure 2-3.

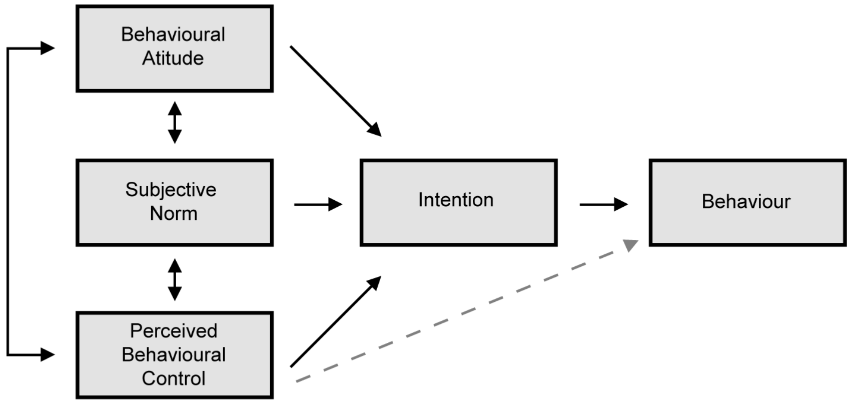

Figure 2-3: Theory of Planned Behaviour (Ajzen, 1991)

According to Azjen (1991), intentions are precursors to behaviours and although there is no perfect relationship between behavioural intention and actual behaviour, TBP relies on the assumption that intention can be used to appropriately represent a behaviour. This observation was one of the most important contributors of the TBP model when compared to previous models of attitude-behaviour relationship, allowing for the variables in this model to be used to determine the effectiveness of interventions even if there is no readily available measure of actual behaviour. This can be considered to be both a strength and a limitation of the TBP. According to Martiskainen (2007) the model is more applicable to measuring the relationships between behavioural constructs rather than measurement of actual behaviour. Yet, in a review of the TBP, Armitage and Conner (2001) concluded that the TBP accounts for considerable proportions of variance in actual behaviour, supporting the TBP as a predictive theory of intentions and behaviours.

2.3 ENERGY CONSUMPTION OF SMALL POWER EQUIPMENT

According to ECG19, electricity consumption for small power equipment will usually represent between 13% and 44% of the total electricity consumption in an office building (CIBSE, 2000). These percentages are likely to increase as buildings become more energy efficient (NBI, 2012). Looking into future climatic scenarios, office buildings are likely to have higher cooling demands due to climate change, emphasizing the need to better understand (and reduce) the impact of internal gains from ICT equipment (Jenkins et al., 2008). 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 ratings will significantly overestimate the casual gains, resulting in the specification of cooling systems with a higher capacity than needed (Komor, 1997). This can result in increased capital cost as well as higher operating costs through part loading (Dunn and Knight, 2005).

Computers are commonly the single biggest source of energy use amongst small power equipment in offices (Carbon Trust, 2006; Moorefield et al., 2011; Wilkins and Hosni, 2011; Lanzisera et al., 2013). Moorefield et al. (2011) conducted a monitoring study of small power use in 25 offices in California over a 2-week period. Power demand data for 470 plug load devices was collected at 1-minute intervals through the use of plug monitors and the data were extrapolated based on an inventory of nearly 7,000 devices. Results revealed that computers and screens were responsible for 66% of small power consumption in offices.

2.3.1 COMPUTER ENERGY REQUIREMENTS

Significant improvements in the energy efficiencies of computers have been observed in the last few decades, resulting in reduced energy requirements (Bray, 2006). 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 (EPA, 2012). Published data suggests that newer computers require less energy in 'low power' modes than older computers; meanwhile the demand for computers with increased processing power has resulted in higher power demands when the computers are active (Roberson et al., 2002; Kawamoto et al., 2001). Table 2-1 provides a summary of key published data regarding energy requirement of both laptops and desktops, highlighting these trends. Note that figures for laptop computers exclude the power demand for the in-built screens.

Table 2-1: Published energy requirements figures for desktop and laptop computers

Source	Power Demand (W)					
	Desktop computers			Laptop Computers		
	Active	Low Power	Off	Active	Low Power	Off
Wilkins and McGaffin (1994)	56	56	-	-	-	-
Nordman et al. (1996)	36-55	32-49	0-2	-	-	-
Mungwititkul and Mohanty (1997)	36-48	27	-	-	-	-
Kawamoto et al. (2001)	30-60	25	1-3	12-22	1.5-6	1.5-2
Roberson et al. (2002)	70	9	3	19	3	-
Hosni and Beck (2010)	50-100	-	-	15-40	-	-
Moorefield et al. (2011)	79	3.2	-	74.7	1.6	-

Laptop computers consume only a fraction of the energy of desktop computers, presenting a big opportunity for energy savings in office buildings (Bray, 2006). 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 overall energy consumption of office buildings: laptop shipment figures are projected to be triple that of desktops in the next few years (Meeker et al., 2010). 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 (BECTA, 2006). This technology reduces power demand and resultant heats gains locally by shifting these to centralised processors with higher efficiencies (DEFRA, 2011).

2.3.2 USAGE PATTERNS

Power demand is only one factor affecting the total energy consumption of computers. According to Bray (2006) the way in which a computer is used is arguably a more significant factor in determining the total energy consumption of computers. 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 study into the after-hours power status of office equipment highlighted a significant variation amongst the number of computers switched off at the end of the day, ranging from 5% to 67% (Webber et al., 2006). Amongst the monitored computers, the rate of after-hours turn off was larger for laptops than desktops.

Focusing on daytime usage, Kawamoto et al., (2004) suggested that on average, the monitored computers were powered on for 6.9 hours a day, being in active mode for 3 hours per day). Studies dating back to the 90's suggest that on average, computers are active for approximately 9% of the year (Mungwititkul and Mohanty, 1997). In a detailed monitoring study of 3 desktop computers, Nordman et al. (1996) calculated that computers were active between 17-31% of the time during workdays, falling to 9-16% when all days were considered. More recently, Moorefield et al. (2011) monitored 61 desktops and 20 laptop computers in-use in 25 offices in California over a two-week period. 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.

2.3.3 POWER MANAGEMENT

Power management settings can also have a significant impact on the energy consumption of computers, influencing the amount of time a computer spends on different operating modes (NBI, 2012). 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 minutes of inactivity, 76% of the idle time would be spent on low power mode (Kawamoto et al., 2004). Alternatively, setting the time delay to 60 minutes resulted in the computer only spending 20% of its idle time in low power mode. A study carried out by the Australian National Appliance and Equipment Energy Efficiency Program (NAEEEP) revealed that aggressive power management (powering down computers after 5 minutes of inactivity) resulted in a reduction of annual energy consumption by approximately 75% compared to a scenario when no power management settings were applied (NAEEEP, 2003).

2.3.4 USAGE DIVERSITY

When estimating the peak demand and energy consumption of computers, usage diversity should also be considered (Parsloe and Hebab, 1992). Actual peak demand for computers (and subsequent energy consumption) in a given area of a building will be less than the sum of power demand for each computer due to usage diversity (Wilkins and Hosni, 2000). Diversity factors need to be applied to load calculations in order to limit oversizing of cooling plants (Komor, 1997). 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 (Wilkins and McGaffin, 1994). 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 to 78% (Wilkins and McGaffin, 1994). More recently, Wilkins and Hosni (2011) 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. Measured diversity during weekends were observed to be 10% and 30% for computers and screens, respectively (Wilkins and Hosni, 2011).

2.3.5 CHANGES TO THE WORKPLACE

The past decade has seen a major shift towards flexible working practices in both private and public sectors fueled by tougher markets and technological advances (Myerson and Ross, 2006). 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 at meetings, 'on the road' or working remotely (Fleming, 2011). 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 development of workplaces also suggest that further reliance on ICT is likely to occur regardless of the adoption of flexible working practices (Worthington, 2005).

A recent study by Johnston et al. (2011) modelled the impact of two possible future scenarios for computer use in office buildings: (i) an energy conscious scenario where ICT acquisition policy is driven by an effort to minimize energy consumption and carbon emissions; and (ii) a 'techno explosion' scenario where maximisation of productivity gives users freedom to select the level of ICT 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.

2.4 SUMMARY

This literature review has assessed the role and shortcomings of Building Regulations in England and Wales, highlighting that the reliance on simplified energy models often results in unrealistic expectations of building performance. Compliance calculations exclude numerous sources of energy use such as small power equipment, contributing to significant discrepancies between design stage calculations and operational performance. The lack of data pertaining to the energy performance of buildings in-use is also likely to be a major contributor to this gap in performance. Recent initiatives have raised the awareness of such issues highlighting that predictions of operational energy use can only be made if the building is modelled as it is expected to operate. This is a great challenge to the industry as the efficient operation of buildings falls beyond the responsibility and control of the designer.

Occupant behaviour was highlighted as an important variable influencing the operational energy performance of buildings. Research into the domestic sector successfully quantified the extent of this impact using a survey based on the Theory of Planned Behaviour (TPB). A review of this method and underlying principles was conducted highlighting the potential to apply a similar methodology in the assessment of variation in energy performance of office buildings.

A review of existing literature on the impact of small power equipment on the energy performance of office buildings was undertaken focusing mainly on computers. This revealed fast-paced changes to ICT equipment, illustrating a trend towards higher energy requirements in active modes of operation and lower requirements at ‘low power’ modes. The review also highlighted the importance of considering usage patterns, power management settings and diversity of use when establishing energy consumption levels. Recent changes to the workplace have resulted in greater reliance on computers, and further changes to the working practices are anticipated. There is scope to investigate the factors influencing the energy consumption of computers in more detail, especially with regards to user behaviour.

3 RESEARCH METHODOLOGY

This chapter summarises the development and application of a suitable research methodology for addressing the research objectives outlined in Section 1.3, providing a systematic route for conducting the research. The EngD programme requires that the project demonstrates innovation in the application of knowledge to the engineering business environment, resulting in the need for an applied approach to research. Some of the most commonly used methodologies include: ethnographic, case study, experimental, survey and action research (Robson, 2011). A case study approach was deemed to be the most appropriate choice, as it allows for an empirical investigation of a contemporary phenomenon within its real-life context (Yin, 2008).

Robson (2011) discusses the differences between applied research and experimental research design, highlighting that the manipulation of a single variable in laboratory conditions is impractical in the 'real world' due to the large number of complex variables. According to Robson (2011), a case study approach is particularly beneficial when a phenomenon needs to be investigated in context, especially where the boundary between phenomenon and its context are not clear. This is of particular benefit when considering the dynamic and commercial nature of the business environment in which an EngD is set, as it recognises the need for an exploratory approach, enabling a flexible research design. According to Yin (2008), case studies are one of the most common methods of conducting research in business, allowing for complex multivariate conditions to be investigated. Brown (2008) claims that the scope of a case study is bounded and the findings can rarely be generalised; yet as a method, it can provide rich and significant insights into events and behaviours, increasing the understanding of a particular phenomenon.

3.1 OVERVIEW OF THE METHODOLOGICAL APPROACH

A key element of the EngD programme is that the project must allow for 'thinking stages' whereby the researcher is expected to critically analyse the work undertaken and define an action plan for continual progression (CICE, 2012). This approach is aligned with O'Leary's cycles of research, illustrated in Figure 3-1 (Koshy et al., 2010).

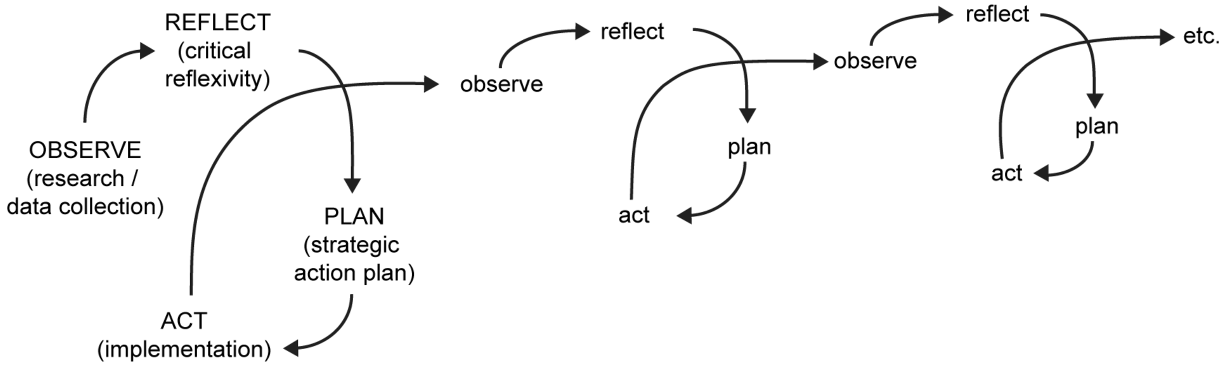

Figure 3-1: O'Leary's cycles of research (adapted from Koshy et al., 2010)

Figure 3-2 illustrates the key stages in the research process for this EngD, highlighting the cyclic nature of the methodology focused on observations, reflections, planning and actions (feeding back into observations and so forth). This process allowed for six focused projects to be carried out after which critical decisions were made regarding the direction of the research based on the key outcomes. By rationalising the research project in this way, the researcher was also able to provide a consistent turnaround of deliverables to the sponsor company as well as timely publication of research outcomes. Each study (numbered 1-6 in the diagram) is discussed in detail in Section 4. Studies 1-4 have been published either as a conference or journal paper. Study 5 was used to inform the work undertaken in Study 6, which has recently been submitted to the journal Energy and Buildings.

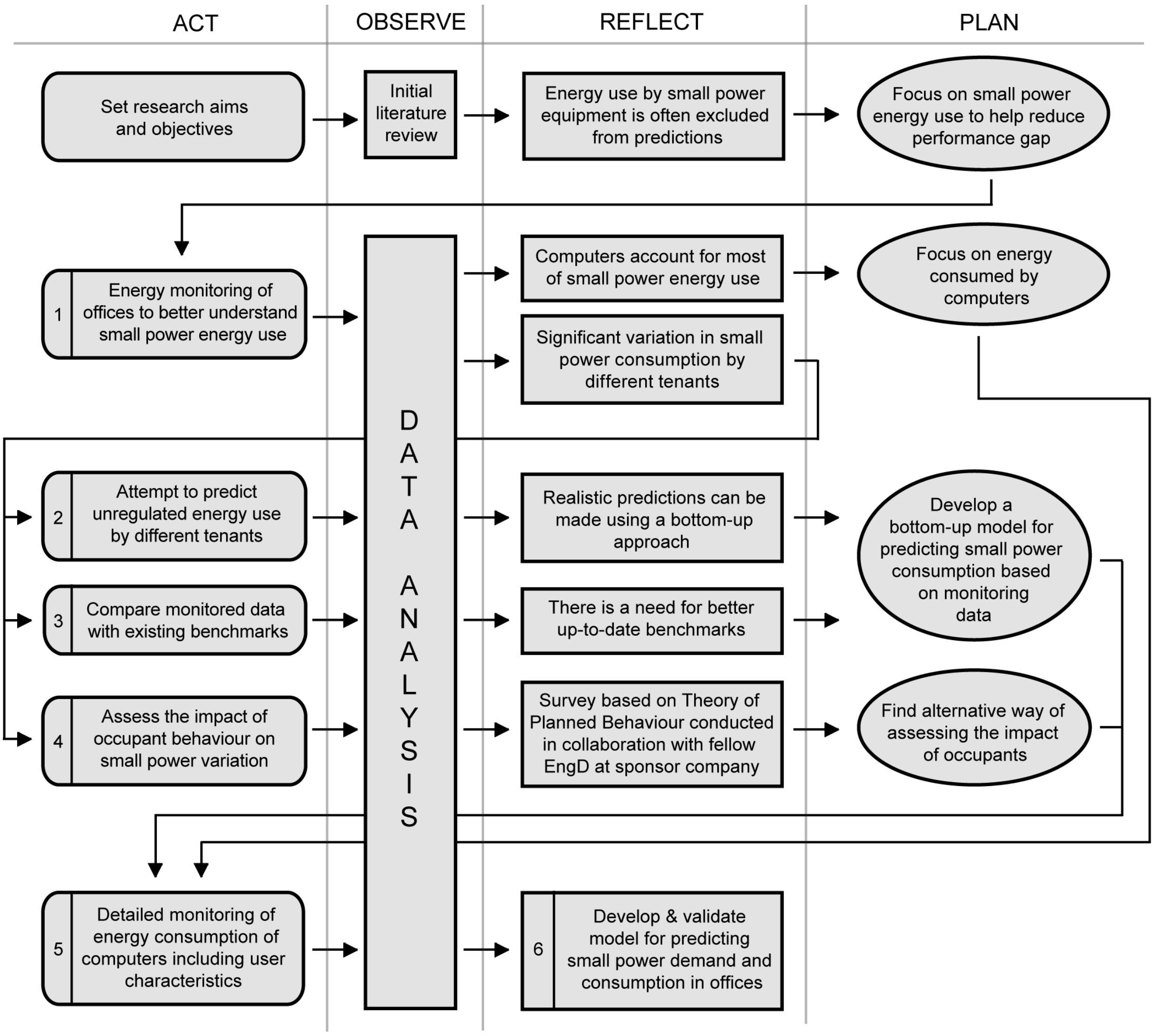

Figure 3-2: Research map detailing the processes undertaken during the research project

3.2 METHODS USED

Numerous methods were implemented in this research project and these are discussed below. Each individual method addresses a different requirement for data collection and/or analysis. Table 3-1 summarises which methods were used in each of the studies illustrated and numbered in Figure 3-2.

Table 3-1: Summary of methods/tools used in each study

		Study 1	Study 2	Study 3	Study 4	Study 5	Study 6
Literature Review		✓	✓	✓	✓	✓	✓
Energy Surveys	**Walk-through Audit**	✓	✓	✗	✓	✗	✓
	Meter Readings	✓	✓	✗	✓	✗	✓
	Sub-circuit Level Power Demand Monitoring	✓	✓	✗	✗	✗	✓
	Equipment Level Power Demand Monitoring	✓	✓	✓	✗	✓	✓
Behavioural Survey		✗	✗	✗	✓	✗	✗
Analysis of Monitored Data	**Energy Consumption**	✓	✓	✗	✓	✓	✓
	Time Series Profiles	✓	✓	✓	✗	✓	✓
	Mean Power Demand	✗	✗	✓	✗	✓	✗
	Time Spent	✗	✗	✗	✗	✓	✗
	Uncertainty Analysis	✗	✗	✗	✗	✓	✓
	'Window-plots'	✗	✗	✗	✗	✓	✗

3.2.1 LITERATURE REVIEW

A literature review is a fundamental method in any research project, highlighting previous and parallel research efforts related to the research topic, providing a foundation for the work to be carried out. The main objectives of a literature review include (Robson, 2011):

- exposing gaps in knowledge and identifying principal areas of dispute and uncertainty;
- identifying general patterns to findings from multiple examples of research in the area;
- defining appropriate research methodologies and methods.

An extensive literature review was carried out at the beginning of the project, being supplemented by further reviews throughout the duration of the research. These addressed the specific needs of the individual studies whilst also ensuring that parallel publications were considered as they became available. Chapter 0 provided an overview of the key outcomes of the literature review conducted as part of the research project. Further literature review can also be found within each of the publications included in the Appendices.

3.2.2 ENERGY SURVEYS

CIBSE TM22 sets out a methodology for assessing the energy and systems performance of a building (CIBSE, 2006a). The procedure is based on work carried out by Field et al. (1997) and was implemented throughout the PROBE studies (discussed in Section 2.2.2), allowing energy consumption to be broken down into a number of end-use categories. These include two categories of particular interest to this EngD: (i) office equipment; and (ii) local kitchens and vending. From a sub-metering perspective; it is often not possible to disaggregate both these end-uses as they are commonly included in the same electricity sub-circuit. Hence, the commonly used term 'small power' is used as an end-use category throughout this thesis, accounting for office equipment and local catering equipment, as well as miscellaneous plug loads.

The methods implemented in this research project are based on CIBSE TM22 and its underlying bottom up tree-diagram approach illustrated in Figure 3-3. The level of sub-metering in a building will dictate the amount of 'high-level' information that can be used to initially assess the energy performance of the building. The information shown in Figure 3-3, labelled A and B can typically be obtained from a combination of readings from individual electricity meters and sub-meters. The methodology then provides a framework for estimating the expected energy consumption of individual end-uses through a bottom-up approach based on the information in boxes C through H. These are generally obtained from design documentation and an in-depth understanding of how the building is used and managed including operating hours and management characteristics. Regular reviews of bottom-up calculations must be carried out to ensure reconciliation with metered data.

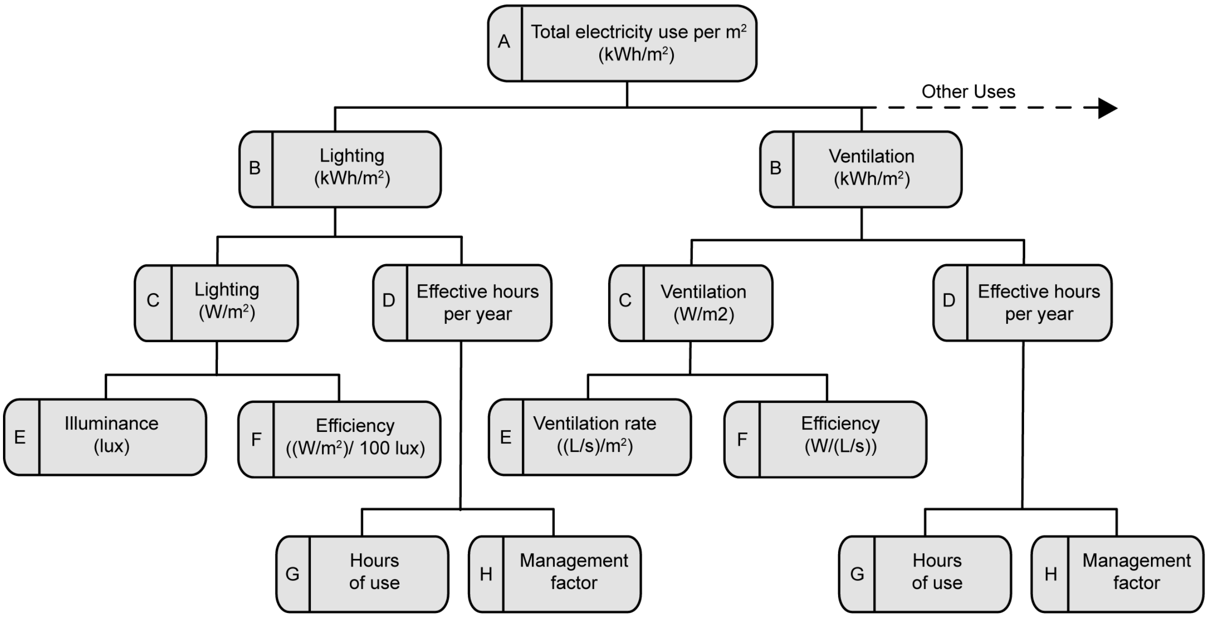

Figure 3-3: CIBSE TM22 approach for analysing energy consumption in buildings

When dealing with individual items of equipment, the TM22 methodology relies on a combination of nameplate ratings and electrical load factors to estimate the actual load of the equipment. Nameplate ratings refer to the maximum load of a device and an electrical load factor is often used to convert the rated load into a more usable 'typical' power demand value. Although this is an appropriate method for major pieces of equipment such as chillers and fans, nameplate ratings are notoriously unrepresentative of the actual power demand of small power equipment (as discussed in Section 2.3). Moreover, electrical load factors can be difficult to accurately estimate without a detailed understanding of the installed equipment specification. As such, an alternative method was employed when assessing the power demand and electricity consumption of small power equipment (see Section 3.2.2.4).

It is worth noting, CIBSE TM22 provides a flexible framework that can be tailored to suit the specific objectives of the assessment. As such, a number of additional and harmonising methods were used throughout the research project to complement the underlying principles of CIBSE TM22. These are detailed below.

3.2.2.1 Walkthrough Audit

A walk-through survey is typically the first step in any energy audit, consisting of an exploratory site visit to visually inspect each of the energy using systems (Thumann et al., 2009). Focusing on small power equipment, walkthrough surveys were used throughout this EngD to provide an assessment of the installed equipment throughout the building, allowing for detailed inventories to be produced regarding the types and quantities of installed appliances in individual building zones.

3.2.2.2 Meter Readings

Meter readings provide valuable information regarding the consumption of electricity over a given period of time. Depending on the sub-metering of a building, meter readings can provide further insight to the energy consumption of specific end-uses and/or individual zones. Sub-metering by zone is a common feature in most multi-tenanted office buildings allowing for individual tenants to be billed for their electricity consumption. This is usually based on monthly meter readings obtained by facilities managers. Buildings with Automatic Meter Reading (AMR) systems allow for electricity demand to be monitored in shorter intervals (typically half-hourly or 15-minutely). This can be particularly useful in order to analyse the variation in electricity consumption over a given day.

3.2.2.3 Power Demand Monitoring at Sub-circuit Level

When appropriate sub-metering is not available, electricity consumption can be measured at a sub-circuit level using a portable electrical energy profile logger such as ‘El Component SP Max’ (used in this research project). This piece of equipment monitors power using current and voltage transducers, and has a published accuracy of 0.25% on primary parameters. It can be used to monitor most sub-circuits by connecting current transformers to a low voltage panel or distribution board. However, there are practical limitations to the use of this monitoring technique as it is not possible to disaggregate separate end-uses that have electricity supplied through the same sub-circuit, and electricity is often supplied for lighting and small power through a single sub-circuit in office buildings (Lanzisera et al., 2013).

3.2.2.4 Power Demand Monitoring at Equipment Level

Electricity consumption and power demand can be measured and monitored at individual equipment level through the use of plug monitors with logging capabilities. According to Lanzisera et al. (2013), this novel type of monitoring is considered the best method for collecting energy data of small power equipment, providing high quality data at the device level, which can be extrapolated through the use of inventories of installed equipment to achieve higher level data. Class-1 accuracy ‘Telegesis ZigBee Plogg-ZGB’ plug monitors were used throughout this research project and have a published measurement uncertainty of <0.5%. These monitoring devices can measure and record power demand in time intervals of 1-minute, yet they have limited internal memory capabilities. In order to increase the capacity for data storage, monitored data can be wirelessly transmitted and downloaded to a computer, yet this must be located within approximately 10 metres of the ‘Ploggs’ in order to ensure successful data transfer. Data acquired through equipment level monitoring can also be used to estimate electricity consumption for small power as an end-use by extrapolating the results using detailed inventories of the installed appliances.

3.2.3 BEHAVIOURAL SURVEY

Gill et al. (2010) implemented a novel methodology for quantifying the impact of occupant behaviour on the energy performance of residential buildings based on the Theory of Planned Behaviour (TPB). As discussed in Section 2.2.3, the methodology characterises each contributing behavioural construct (behavioural attitudes, subjective norms and perceived behavioural control) and was used to develop a survey aimed at quantifying the impact of occupant behaviour on the electricity consumption levels in a multi-tenanted office building. Figure 3-4 illustrates this methodology, highlighting key actions taken during the development and implementation of the questionnaire.

Prior to the development of the questionnaire, an elicitation survey was conducted with 30 people outside of the population to be surveyed (i.e. not working in the building under investigation). This consisted of six open-ended questions relating to each of the three predictors to establish the dominant factors that contribute to decisions regarding the target behaviour (as described in Figure 3-4). Respondents were asked to provide three responses to each question and caution was taken to ensure a wide range of backgrounds and age groups were included. The results for the survey were analysed and trivial responses were rejected, ensuring that at least 75% of all beliefs were accounted for. These were then used to develop a multiple choice questionnaire whereby each significant belief was transformed into a question couplet, in line with guidance from Francis et al. (2004). This resulted in a questionnaire with six groups of six questions (i.e. two sections for each predictor of behaviour, with every question having an equivalent couplet). A copy of the questionnaire and further details on the development process can be found in Appendix F.

Scoring scales were established for each group of questions using a 5-point Likert scale as standard. The direction of the scale (i.e. bipolar or unipolar) was determined to suit each set of question groups appropriately. This ensured that each predictor had a unipolar and bipolar group of questions allowing for consistency in the scoring for each predictor.

For the specific study (detailed in Section 4.4), the population of interest was: occupants in a multi-tenanted office building. The next step was to define the behaviour under investigation accounting for the fact that occupants are able to affect electricity consumption in multiple and diverse ways. The key behaviour for investigation was defined as: ‘switching off lighting and appliances when not in use’. This behaviour was deemed appropriately representative of the key interactions between occupant and energy consuming devices in the workplace.

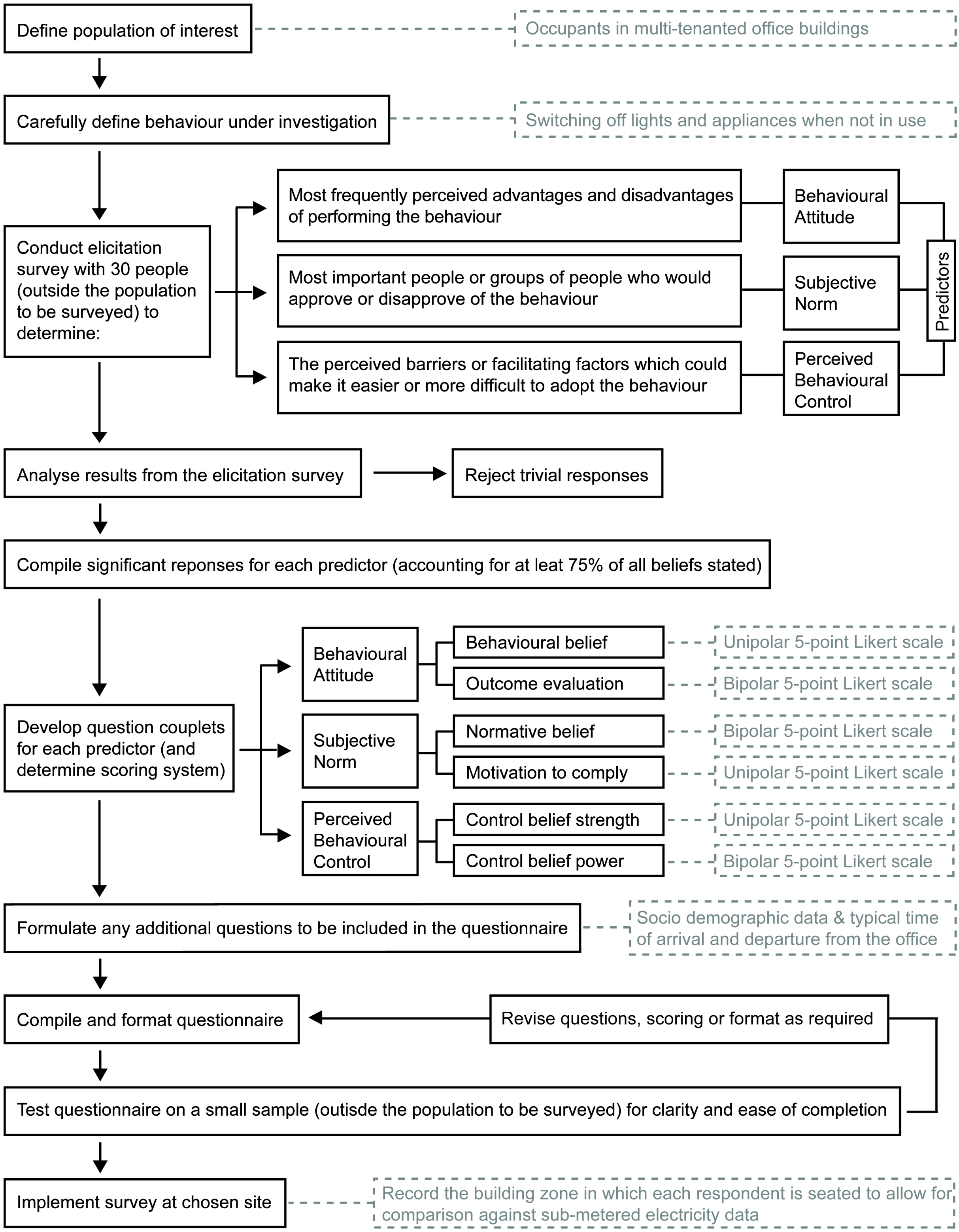

Figure 3-4: Methodology implemented for occupant behaviour study

3.2.4 ANALYSIS OF MONITORED DATA

3.2.4.1 Variation in Energy Consumption

Annual, monthly and daily energy consumption figures (in kWh or Wh) were utilised in this research project. These were acquired via periodical meter readings, AMR or by aggregating power demand monitored data over the given period of time. Annual and monthly consumption figures were used to assess the variability in energy use by different buildings or sub-metered areas of a building. Daily consumption data was used to assess the variation in energy consumption of individual small power equipment. Data analysis took the form of basic summary statistics, including measures of mean, maximum and minimum energy consumption in the sample data. Energy consumption data was also used to illustrate the breakdown of energy use by individual end-uses or equipment types.

3.2.4.2 Time Series Profiles

Time series profiles were used illustrate the variation in power demand (in W or kW) over a 24-hour period. These were plotted in 1-minute, 15-minute, half-hourly or hourly intervals depending on the sample rate of the data. Power demand was normalised by floor area where applicable (in W/m^2 or kW/m^2), allowing for comparison against different buildings/zones as well as benchmarks. Time-series profiles were used to illustrate equipment-level and sub-circuit level power demand data as well as results from predictive modelling.

3.2.4.3 Mean Power Demand

The mean power demand of individual small power equipment was calculated for specific operational modes. Histograms were used to visualise and establish the different modes of operation, as illustrated in Figure 3-5.

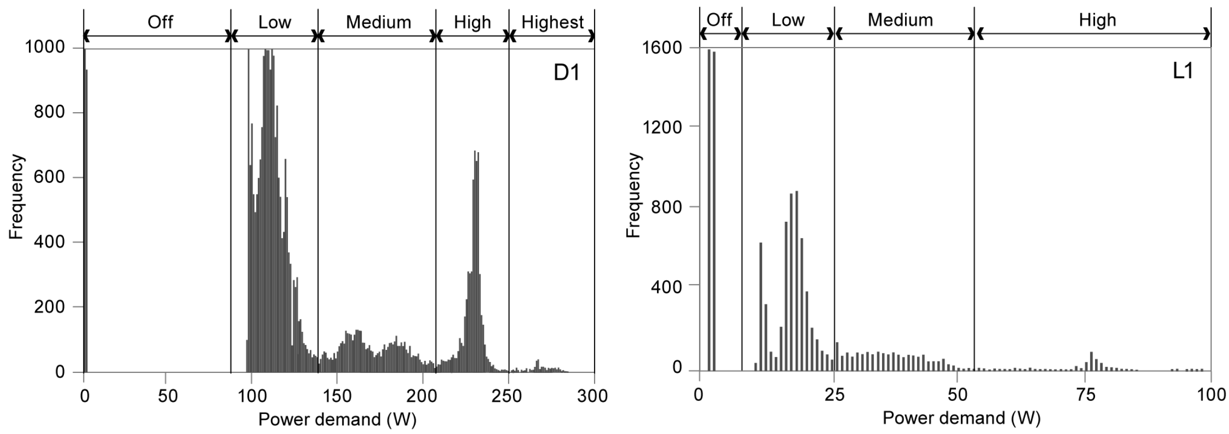

Figure 3-5: Example of histograms used to establish the different operating modes

Moorefield et al. (2011) implemented a similar methodology, determining the modes of operation by statistical grouping of the measured data rather than on characteristics of the internal operation of the equipment. In Study 3, the monitored data was split into two operational modes: ‘stand-by’ and ‘on’ as these were the modes of operation provided in published benchmarks. Study 5 focused solely on computers and up to five operational modes were established: ‘off’, ‘low’, ‘medium’, ‘high’ and ‘highest’. This approach was taken to purposefully steer away from formal operational modes such as ‘idle’, ‘low active’, ‘sleep’, as these are applicable mainly to laboratory testing where the relevant protocols to achieve each mode can be performed and monitored accordingly (EPA, 2009). Considering that this study aimed to assess the performance of computers in use, such formal operational mode definitions would not be applicable. Nonetheless, it is anticipated the ’low’ mode is equivalent to ‘sleep’, being the second lowest recorded mode.

3.2.4.4 Time spent

Once the monitored data was split into individual operational modes, it was possible to calculate the time each computer spent on each mode. The mean time spent ‘on’ and ‘off’ for each machine was also calculated for comparison against published data. In Study 5, the data was then filtered to exclude days in which the computers were not used, as this would skew the results for the mean time spent ‘off’ or on ‘low’ operational modes. The remaining data was also split into typical and atypical days as follows:

- Typical days = full working days (approximately 9am – 6pm)
- Atypical days = either partial days (when the computer was used for less than 5 hours) or over an extended period of time (e.g. when the computer was operational overnight).

This approach provided an additional layer of analysis, allowing for the assessment of variability on working days of similar duration.

3.2.4.5 Uncertainty analysis

The uncertainty in mean power demand and time spent on each mode was calculated using Student’s t distribution, illustrating the 95% prediction intervals as follows (Coleman, 2009):

$$u = t.S\sqrt{1 + \frac{1}{n}}$$

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

Prediction intervals were calculated instead of confidence limits, as the ultimate aim of the study was to inform better predictions, requiring an estimate of the outcome of future samples.

3.2.4.6 ‘Window-plots’

In order to evaluate the energy consumption and usage patterns of computers, a novel method was developed to aid in the visualisation of the key factors influencing variation. The term ‘window-plot’ is used to describe the outcome of this analysis and is illustrated in Figure 3-6.

As seen, the plot illustrates the mean power demand and time spent on a given mode alongside their calculated uncertainties (as described above).

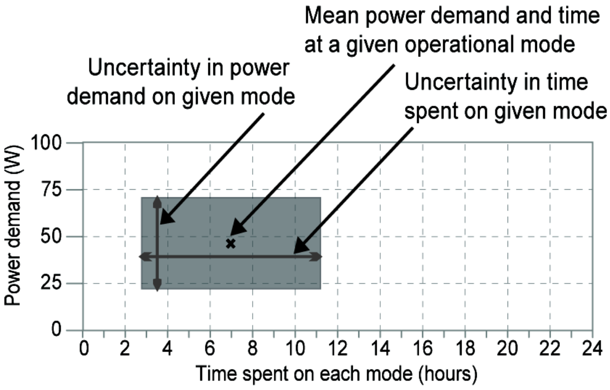

Figure 3-6: Example of window-plot illustrating mean power demand and time spent on each mode as well as uncertainties in each value

4 RESEARCH UNDERTAKEN

This chapter presents the research undertaken to meet the aim and objectives of this thesis. The research was conducted in line with the research methodology presented in Section 3 and refers to the specific research methods detailed in Section 3.2. The chapter is divided into six sub-chapters relating to the six studies undertaken, cross-referencing to the publications produced throughout the EngD. The key publications are included in in the Appendices for further detail.

4.1 STUDY 1: MONITORING ELECTRICITY CONSUMPTION OF SMALL POWER EQUIPMENT

The first study undertaken as part of this EngD addresses Objective 2 of this thesis: "Explore the impact and variability of small power equipment on the operational energy performance of office buildings through post-occupancy studies of multiple tenants". It provides a foundation for addressing the thesis' overarching aim and consists of an initial investigation into the factors that generate variability in small power consumption in commercial buildings.

4.1.1 SCOPE AND AIMS

This study was presented at the CIBSE Technical Symposium 2011 (refer to Appendix A) and provides an analysis of monitored data for electricity consumption by different tenants in two multi-tenanted office buildings. The main aims of the study were to:

- illustrate the extent to which small power equipment contribute towards total electricity consumption;
- assess the variations in electricity consumption by different tenants;
- acquire monitored data for annual small power electricity consumption and daily demand profiles;
- evaluate the impact of different equipment types on small power energy use.

The study focuses on the electricity consumption of small power equipment, yet limitations in the sub-metering strategy of one of the buildings required that lighting electricity consumption be considered in addition to small power demand.

4.1.2 OVERVIEW OF THE STUDY

Two multi-tenanted office buildings were investigated as part of this study, each housing four different tenants, having one tenant in common across both buildings (i.e. seven different tenants in total). Table 4-1 summarises key information about each office building and Table 4-2 provides a summary of the different tenants.

The metering strategy for both buildings is illustrated in Figure 4-1. Both buildings rely on extensive sub-metering to provide adequate breakdown of electricity consumption for billing purposes. In each building, the landlord is responsible for the electricity consumed by all air conditioning equipment and controls, as well as common area lighting and lifts. These end-uses are metered together through a single main incoming meter. The electricity supplied to the tenants is sub-metered by individual floors and/or zones. Each floor is split into 4 zones providing a total of 32 and 16 sub-metered zones in Buildings 1 and 2 respectively. Additional sub-metering in Building 2 allows for further breakdown of electricity consumption into (i) lighting (ii) small power, resulting in a total of 32 tenant sub-meters.

Table 4-1: Key information about the monitored multi-tenanted office buildings

	Building 1	*Building 2*
Location	Central London	Bristol (City Centre)
Number of floors	8	4
Treated floor area per floor (m^2)	2,000 m^2	3,500 m^2
Predominant layout	Open-plan	Open-plan
Air conditioning	Fully air conditioned	Fully air conditioned
Provision of daylight	Glazed façade & atrium	Glazed façade & two atria
Lighting controls	Manual (zoned)	Occupancy & daylight

Table 4-2: Summary of the different tenants occupying the monitored office buildings

Tenant	*Building*	*Occupied floor area (m^2)*	*Type of Business*
A (1)	1	3,761	Engineering consultancy
B	1	4,400	Business data providers
C	1	5,026	Advertising / Marketing
D	1	1,039	Digital communication / Marketing
A (2)	2	1,595	Engineering consultancy
E	2	8,112	Commercial Law firm
F	2	1,158	Service provider
G	2	3,526	Accountancy

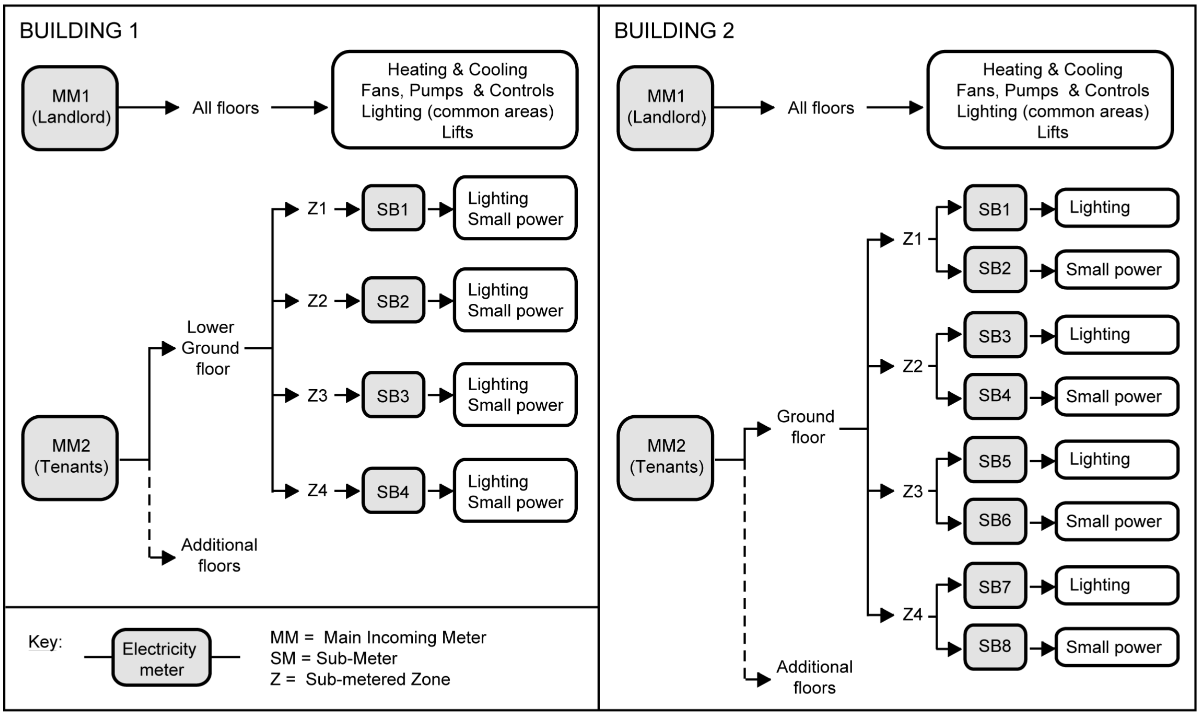

Figure 4-1: Sub-metering strategy for Building 1 and Building 2

Note that the energy consumption of server rooms was excluded from this study (with the exception of Figure 4-2). Most server rooms in the buildings were sub-metered, allowing for their energy use to be subtracted from each tenant's consumption data. Where this was not the case, portable energy profile loggers were used to monitor their electricity consumption over a given week, allowing for annual consumption to be estimated.

The following steps were taken as part of the monitoring process:

1. An assessment of the breakdown of electricity consumption by end-use was conducted in Building 1 in order to provide a contextual basis. This analysis was undertaken in line with the methodology published in CIBSE TM22 (CIBSE, 1999) excluding the fossil fuel consumption (please refer to Section 3.2.2).
2. Monthly meter readings were taken and recorded for each electricity sub-meter in both buildings. Monthly and annual electricity consumption data was then compiled and normalised by floor area, for each zone and tenant.
3. Half hourly demand profiles were obtained for an individual zone in each building (both occupied by Tenant A) using portable energy profile loggers (as described in Section 3.2.2.3) aiming to illustrate potential variations in consumption patterns.
4. Combined plug monitor/loggers were connected to individual items of small power equipment (as described in Section 3.2.2.4) and the monitored energy consumption data was extrapolated for an entire zone based on an inventory of installed equipment.

4.1.3 KEY OUTCOMES

Figure 4-2 displays the breakdown of electricity consumption in Building 1 by end-use. The chart also illustrates split between landlord and tenant consumption, demonstrating that the tenants are responsible for 70% of the building's electricity consumption. Tenant consumption is split into three end-uses: (i) server rooms, (ii) small power and (iii) lighting. Server rooms (including local air conditioning) are the largest consumers at 28%, followed by lighting at 24% and small power at 18%. Although small power is the smallest tenant end-use, it consumed more electricity than the chillers (13%) and fans, pumps and controls (16%). Compared to data published in BRECSU (2000) and Carbon Trust (2010), the breakdown of electricity use in Building 1 is observed to be fairly typical with the exception of servers and fans, pumps and controls; the former being higher and the latter being lower than the benchmark office buildings.

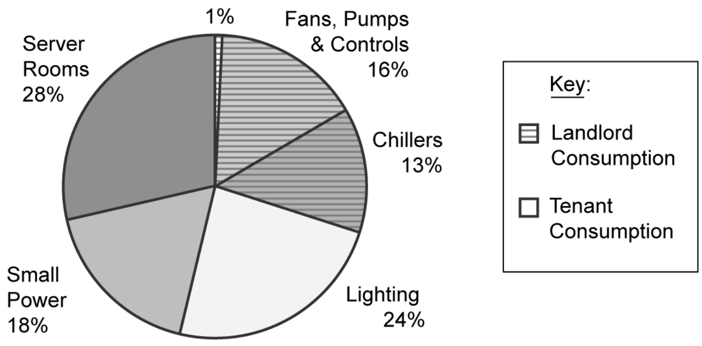

Figure 4-2: Breakdown of electricity consumption by end-use

Figure 4-3 illustrates the annual electricity consumed by each tenant for lighting and small power (broken down into the individual end-uses where possible) alongside existing typical (TYP) and best-practice (BP) benchmarks published in ECG19 (BRECSU, 2000). Significant variations in electricity consumption are observed with the highest consuming tenant (B) using 72% more electricity per year than the lowest consuming tenant (F). Focusing on small power consumption, Tenant A2 consumes 73% more electricity than the lowest consuming tenant (G). Generally, the tenants occupying Building 2 are in the lower consuming half of the graph and this could be attributed to the building's more comprehensive lighting controls (relying both on daylight dimming and occupancy presence detectors). This assumption can be substantiated by the fact that all Building 2 tenants have an annual lighting consumption below the typical benchmark. Yet, significant variations in lighting consumption are observed, being attributed to two elements: (i) hours of occupancy; and (ii) location of occupied zones. The tenant with the lowest annual consumption for lighting (F) only occupies zones in the perimeter of the building and also has strict hours of operation limited from 9am to 6pm. Walkthrough surveys and further analysis of the variation in energy consumption in individual zones revealed that the areas with lowest electricity consumption for small power were more sparsely occupied and generally included meeting rooms and/or reception areas with low densities of ICT equipment.

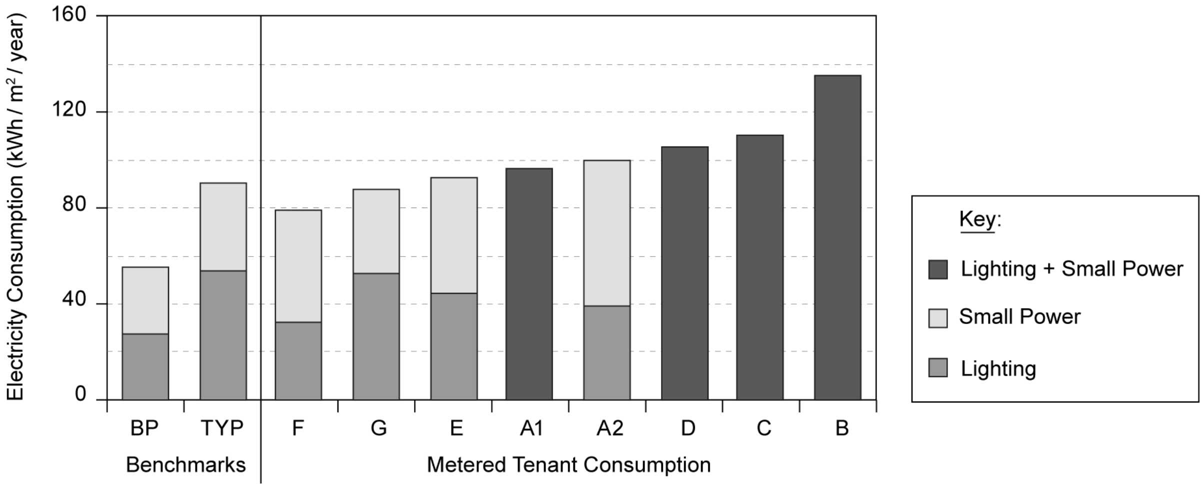

Figure 4-3: Annual electricity consumption by different tenants compared to benchmarks

Informal interviews with the building occupants revealed a number of behavioural elements that are likely to contribute towards the variation in electricity consumption for small power equipment. Notable observations included:

- the highest consuming tenant (B) operates an IT upgrade and maintenance policy whereby all computers must be kept on overnight;
- the business nature of Tenant C (the second highest consuming tenant) results in employees often leaving their computers running overnight in order to run high quality graphical rendering;
- the lowest consuming tenants in Building 1 (A and D) and the tenant with the lowest small power consumption in Building 2 (G) encourage their employees to switch off office equipment at the end of each day.

Focusing on the tenant that occupies zones in both building (A), their electricity consumption is fairly consistent in both buildings, yet they are the highest consumer in Building 2 and the lowest consumer in Building 1.

Figure 4-4 illustrates half-hourly power demand profiles (for lighting and small power) for two zones occupied by Tenant A (one in each building) normalised by floor area over a typical week. Similar profiles are observed in both buildings with demand escalating from around 6am, peaking between 9-10am at around 25 W/m^2 during weekdays. Towards the end of the day, discrepancies are observed whereby demand decreases from 5pm in Building 1, followed by a short peak at around 9pm. This 'late peak' is associated with the cleaning schedule of the building during which period lights are switched back on, multiple vacuum cleaners are used and dishwashers are switched on. No such 'late peak' is observed in Building 2 where cleaning takes place between 6-7pm, extending the power demand which gradually decreases after 7pm. Short periods of occupancy are observed during the weekends in both buildings. Regarding base loads, Building 2 has a lower demand at approximately 3W/m^2 compared to 6W/m^2 in Building 1.

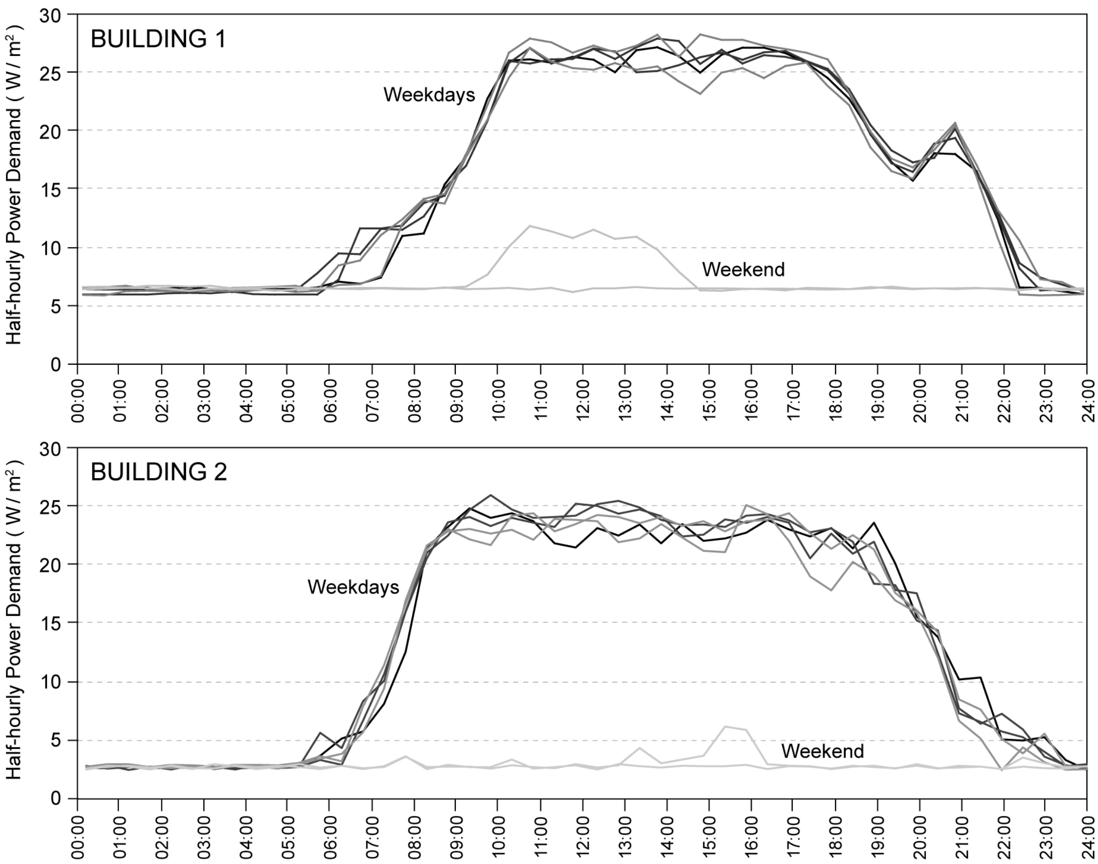

Figure 4-4: Half-hourly electricity demand profile for lighting and small power

Figure 4-5 illustrates the annual electricity consumption by different types of small power equipment in all zones occupied by Tenant A in Building 1. As seen, computers are responsible for the largest proportion of electricity consumption at 17.5 kWh/m^2 followed by computer screens at 14.6 kWh/m^2, cumulatively accounting for more than 60% of the annual electricity consumption. Photocopiers are estimated to consume 6.2 kWh/m^2 per year, with the remaining types of equipment accounting for less than 2 kWh/m^2 each.

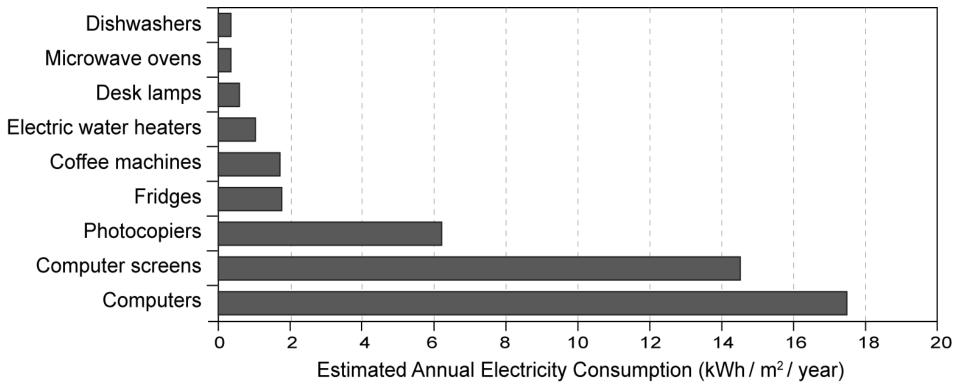

Figure 4-5: Estimated annual electricity consumption per different types of equipment

4.1.4 SUMMARY

This study has highlighted that variations up to 72% occur in annual electricity consumption for lighting and small power amongst different tenants occupying two multi-tenanted office buildings. Small power consumption by tenants occupying the same building varied by up to 73%. Variations in space layout, density of IT equipment, lighting controls and the availability of daylight are likely to be the key physical influencing factors. Behavioural and management factors such as occupancy hours and the decisions surrounding the operation of computers outside of working hours were also observed to have an influence on electricity consumption. Analysis of a tenant occupying zones in both buildings suggest that the working practices, attitudes and behaviours of a company might transcend the immediate surroundings of the building being occupied, demonstrating similar annual consumptions and power demand profiles.

Overall the study has demonstrated not only that small power is a significant energy end-use in office buildings but also that it can vary substantially amongst different tenants. This finding substantiates the need for representative, building specific estimates of small power consumption. The study also suggests a need for better understanding of occupancy patterns and behaviour in office buildings, as these were observed to be contributing factors to variations in energy consumption.

4.2 STUDY 2: ESTIMATING ELECTRICITY CONSUMPTION FOR SMALL POWER AND LIGHTING IN A MULTI-TENANTED OFFICE BUILDING

The second study undertaken as part of this EngD builds on from Study 1 and assesses the potential for using Post-Occupancy Evaluation (POE) data to inform better estimates of small power energy use. The study addresses the overarching aim of this thesis by demonstrating different ways in which small power can be accounted for in estimates of energy-use, whilst also providing further insight into the factors that generate variability in small power consumption. Data acquired in Study 1 was complemented by additional monitored data focused mainly on the installed equipment and occupancy patterns of two zones occupied by different tenants. Five models were developed for each zone with increasing levels of POE data being used to estimate small power and lighting consumption.

4.2.1 SCOPE AND AIMS

This study was presented at the Third International Conference on Applied Energy (in 2011), being subsequently selected for inclusion in a special edition of the Applied Energy Journal (refer to Appendix B). The study builds on the analysis of lighting and small power energy consumption for Building 1 detailed in Section 4.1 and aims to:

- provide further insight into the impact of occupancy patterns on energy consumption;
- attempt to estimate the energy consumption for lighting and small power by different tenants occupying the same building based on increasing levels of monitored data.

4.2.2 OVERVIEW OF THE STUDY

Building on from Study 1 (detailed in Section 4.1), further data regarding occupancy patterns, installed equipment and design stage specifications in the two zones were undertaken as follows:

1. Occupancy patterns were monitored in a given zone occupied by Tenant A by manually recording the number of occupants present in the zone in half-hour intervals.
2. A detailed walkthrough survey was undertaken in two zones in the building occupied by Tenants A and B to record the number and types of office and catering equipment installed as well as lighting fixtures (refer to Section 3.2.2.1).
3. Plug monitors were used to monitor the power demand of a representative sample of equipment installed in the zone occupied by Tenant B in 5-minute intervals to complement the data acquired for Tenant A in the previous study.
4. Lighting specifications were obtained to estimate the expected energy consumption at design stage.

The acquired information was used to produce a set of predictive models for annual electricity consumption in both zones. An increasing level of detail was used in each subsequent model, replacing typical assumptions with monitored data as described in Table 4-3.

Table 4-3: The five predictive models developed

Model	Brief description
1	Typical compliance model using lighting specification from the design brief, using SBEM standard occupancy hours and overlooking small power and catering equipment.
2	'Enhanced' compliance model using industry rules of thumb to account for small power loads (BSRIA, 2011) but overlooking catering equipment.
3	Initial bespoke model using installed lighting loads as well as measured electricity demand for basic small power and catering equipment. SBEM standard occupancy hours were used accounting for an 80% usage factor of small power equipment.
4	Intermediate bespoke model using installed lighting loads (including task & decorative lighting) as well as measured electricity demand for all small power and catering equipment installed. SBEM standard occupancy hours were used once again with allowances for usage factor of small power equipment.
5	Advanced bespoke model using installed lighting loads (including task & decorative lighting) as well as measured electricity demand for all small power and catering equipment installed. Monitored hours of use were used for all lighting, small power and catering equipment.

Table 4-4: Input parameters used in each model

	Tenant A			Tenant B		
Model	**Lighting**	**Office Equipment**	**Catering**	**Lighting**	**Office Equipment**	**Catering**
1	11 W/m^2 2600 hrs/year	Not considered	Not considered	11 W/m^2 2600 hrs/year	Not considered.	Not considered.
2	11 W/m^2 2600 hrs/year	15W/m^2 2080 hrs/year (due to 80% usage factor)	Not considered	11 W/m^2 2600 hrs/year	15 W/m^2 2080 hrs/year (due to 80% usage factor)	Not considered.
3	13 W/m^2 2600 hrs/year	170 laptops 170 screens 5 printers = 11 W/m^2 2080 hrs/year	1 water heater 1 fridge = 0.3 W/m^2 2600 hrs/year	12.8 W/m^2 2600 hrs/year	40 laptops 70 desktops 110 screens 4 printers = 11.6 W/m^2 2080 hrs/year	1 water heater 1 fridge = 0.3 W/m^2 2600 hrs/year
4	13 W/m^2 2600 hrs/year	170 laptops 170 screens 5 printers 8 desk lamps 6 desk fans = 11.5 W/m^2 2080 hrs/year	1 water heater 1 fridge 1 microwave 1 dishwasher 2 coffee machines = 1 W/m^2 2600 hrs/year	17.3 W/m^2 2600 hrs/year	40 laptops 70 desktops 110 screens 4 printers 2 desktop printers 3 plasma TVs = 12.6 W/m^2 2080 hrs/year	1 water heater 1 fridge 3 glass front fridges 2 microwave 1 dishwasher 2 coffee machines 2 vending machines = 2.3 W/m^2 2600 hrs/year
5	13 W/m^2 3640 hrs/year	170 laptops 170 screens 5 printers 8 desk lamps 6 desk fans = 11.5 W/m^2 [monitored hours of use per individual equipment]	1 water heater 1 fridge 1 microwave 1 dishwasher 2 coffee machines = 1 W/m^2 [monitored hours of use per individual equipment]	17.3 W/m^2 3120 hrs/year	40 laptops 70 desktops 110 screens 4 printers 2 desktop printers 3 plasma TVs = 12.6 W/m^2 [monitored hours of use per equipment]	1 water heater 1 fridge 3 glass front fridges 2 microwave 1 dishwasher 2 coffee machines 2 vending machines = 2.3 W/m^2 [monitored hours of use per equipment]

Table 4-4 provides a summary of the key input parameters for each predictive model. These include inputs for lighting, office equipment and catering (where applicable) and deals with high level power demand values (per m^2), equipment quantities (used in combination with monitored power demand at equipment level) and hours of operation (per year).

A 'bottom-up' approach was used to produce the predictive models in line with the methodology detailed in CIBSE TM22 (CIBSE, 1999). This methodology has previously been used to predict electricity consumption (Bordass et al., 2004; Cohen et al., 2006), relying on the use of nameplate ratings to estimate the energy consumption of equipment. In this study however, nameplate ratings were replaced with monitored power data for the individual appliances in order to estimate the annual energy consumption of office and catering equipment.

4.2.3 KEY OUTCOMES

Figure 4-6 illustrates the relationship between monitored electricity demand and occupancy levels for a zone occupied by Tenant A on a typical day. As shown, electricity demand generally follows the monitored occupancy with two exceptions:

- A significant reduction in occupancy levels is observed around lunchtime yet electricity demand reduces only slightly. This is consistent with the fact that lighting levels remain constant and most office equipment is kept on during lunch breaks. Due to power management settings, most computer screens will switch off after 15-minutes of inactivity and this is likely to result in the slight drop in electricity demand.
- A spike in electricity around 9pm is observed due to the cleaning schedule of the building (as described in Section 4.1.3). Occupancy levels are minimal at this point as only 2 cleaners are present in the zone.

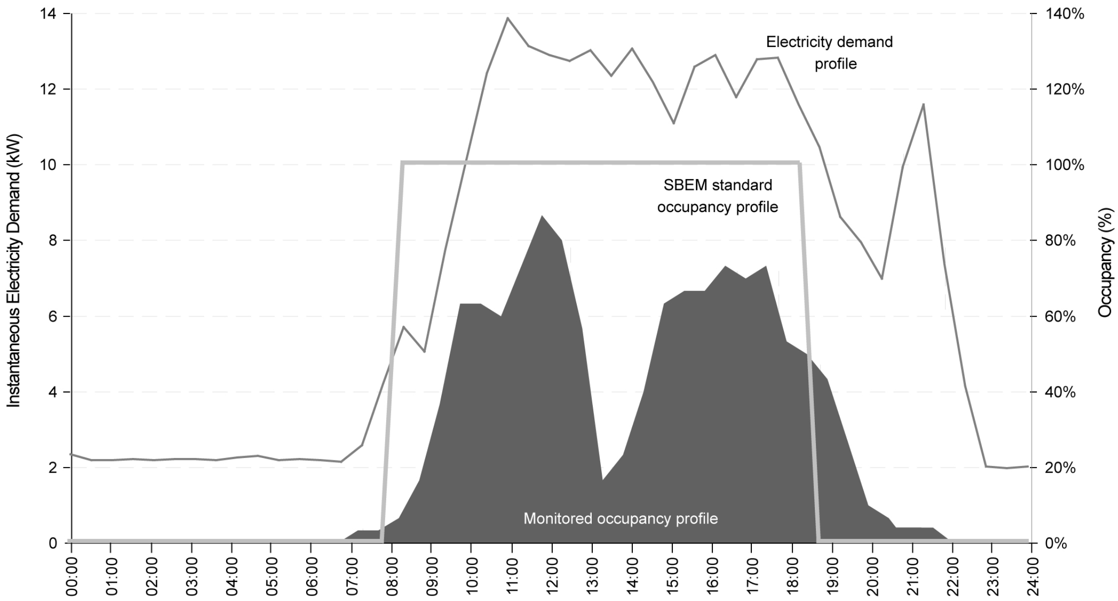

Figure 4-6: Relationship between monitored electricity demand and occupancy profiles.

Figure 4-6 also illustrates the standard occupancy profile for offices used in Simplified Building Energy Models (SBEM) for compliance with Part L of the Building Regulations. Despite its simplistic nature for compliance purposes, standard profiles such as this are normally used in Dynamic Simulation Models (DSMs), yet there is little correlation between the SBEM profile and the monitored electricity consumption.

Figure 4-7 illustrates the results for each of the 5 models as well as the actual electricity consumption in both zones. Model 1 relies on assumptions for a typical compliance model providing the same results for both zones, accounting only for lighting energy use, being equivalent to less than 30% of the actual electricity consumption in both cases. Results for Model 2 rely on rules of thumb for estimating small power consumption, increasing the estimates to 58% and 47% of the actual electricity consumption for Tenants A and B respectively. Models 3 and 4 rely on increased levels of monitored data to inform estimates for lighting, office and catering equipment, gradually increasing the estimated annual consumption figures. Model 5 relies on the same input parameters as Model 4 yet assumes realistic occupancy hours based on monitored data rather than using SBEM occupancy profiles. Arguably, the final model is an estimate based on the extrapolation of monitored data rather than a predictive model, yet the final results account for 97% and 94% of the actual electricity consumption for Tenants A and B, respectively.

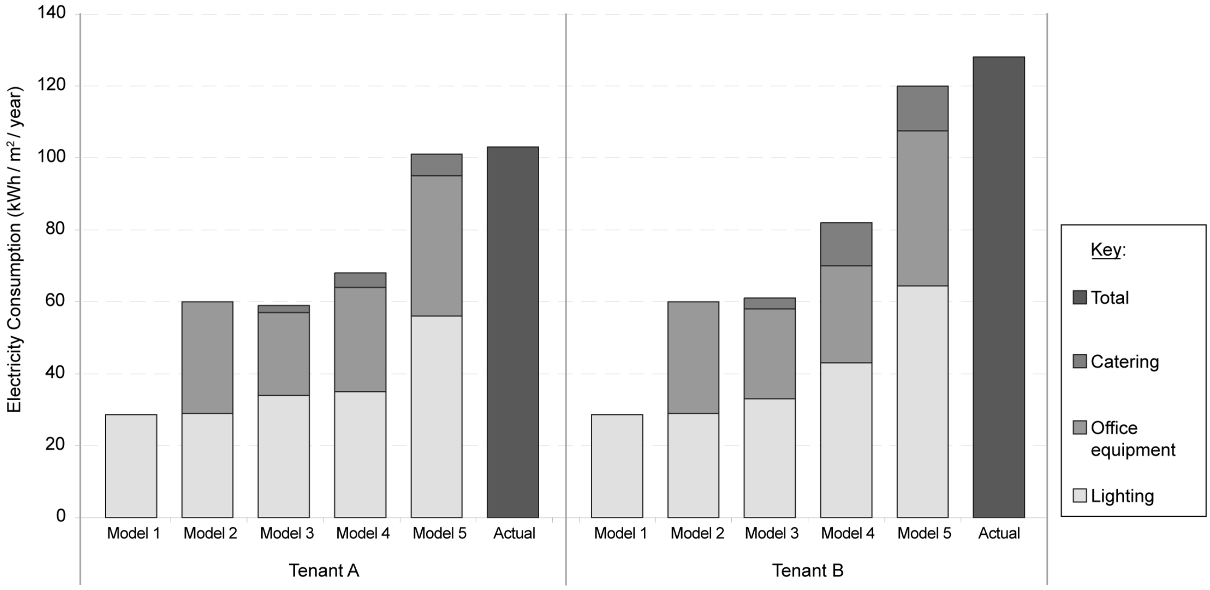

Figure 4-7: Predictive model results and actual electricity consumption in the zones investigated.

4.2.4 SUMMARY

This study has highlighted the potential for using knowledge acquired from Post-Occupancy Evaluations (POE) to inform better predictions of energy use. Results revealed that by using POE data, electricity consumption of lighting and small power can be estimated to within 6% of actual consumption (in the case study building). Despite the limited applicability of this methodology to non-speculative buildings, the results are encouraging and demonstrate that reliable predictions can be obtained for lighting and small power loads by replacing assumptions in the modelling process with realistic inputs based on POE data. In addition, a clear correlation was observed between monitored occupancy profiles and tenant electricity consumption, highlighting the importance of using realistic occupancy hours when predicting electricity consumption.

Overall the study has demonstrated the limitations of current compliance modelling techniques. The use of high-level benchmarks in W/m^2 presents an improvement over basic compliance calculations, yet this approach fails to account for the variability of small power use by different tenants. When coupled with NCM occupancy hours, the high-level benchmark underestimates energy consumption in both zones investigated. These findings further substantiate the need for representative, building specific estimates of small power consumption that take into account the types and quantities of installed equipment as well as realistic hours of operation.

4.3 STUDY 3: COMPARING MONITORED DATA TO INDUSTRY BENCHMARKS FOR SMALL POWER EQUIPMENT

The third study undertaken as part of this EngD addresses research Objective 3: "Assess whether industry benchmarks are representative of small power equipment currently being used in office buildings". It provides a critical evaluation of benchmarks published in CIBSE Guide F, which are widely used by designers in the UK. These include high-level benchmarks (in W/m^2) as well as equipment level power demand benchmarks (in W) at different operational modes. The focus of the study is on the latter, as they can be used to generate building specific estimates of small power demand and consumption using a 'bottom-up' approach.

4.3.1 SCOPE AND AIMS

This study was presented at the CIBSE ASHRAE Technical Symposium 2012 and provides a comparison of detailed monitored data for small power equipment use in office buildings against industry benchmarks, focusing on the widely used CIBSE Guide F. The paper was selected for inclusion in a special edition of the Journal of Building Services Engineering Research & Technology (refer to 0) by which time a new version of CIBSE Guide F had been published (CIBSE, 2012). As such, the scope of the study covers key benchmarks published in the 2nd edition of Guide F (CIBSE, 2004), which have been widely used by designers over the last 8 years, as well as the updates published its 3rd edition. Data from other sources such as academic papers and reports were also reviewed in order to provide additional context.

The main aims of the study were to:

- review existing benchmarks for small power consumption in office buildings;
- compare benchmarks against monitored data for small power loads in a UK office;
- assess the impact of recent updates to CIBSE Guide F benchmarks;
- provide load profiles for monitored equipment to supplement the published data.

4.3.2 OVERVIEW OF THE STUDY

Table 4-5 displays a set of high-level benchmarks (in W/m^2) originally published in ECG19 (BRECSU, 2000) included in both editions of Guide F. Values for typical (TYP) and Good Practice (GP) demand are provided for the four types of office buildings (previously described in Section 2.1.5). Such benchmarks are useful for addressing installed capacity but fail to account for a number of factors that can influence power demand such as space utilisation, power management and usage diversity (Parsloe and Hebab, 1992). Aiming to address this issue, CIBSE Guide F (both in its 2nd and 3rd editions) provides an alternative methodology for calculating installed loads based on a 'bottom-up' approach. This method was adapted from Energy Consumption Guide 35 (BRECSU, 1993), providing a more robust method for predicting power demand and energy consumption, relying on numerous sources of information, including:

- a list of expected types of equipment;
- typical power consumption figures;
- estimated number of devices;
- proportion of equipment with 'sleep mode' enabled;
- usage diversity; and,
- typical hours of usage for each equipment type.

Table 4-5: High-level benchmarks for office equipment

	Type 1		Type 2		Type 3		Type 4	
	GP	TYP	GP	TYP	GP	TYP	GP	TYP
Installed capacity: floor area with ICT (W/m^2)	10	12	12	14	14	16	15	18
Annual running hours (1000 of hours)	2	2.5	2.5	3	2.75	3.25	3.0	3.5
ICT area as % of treated floor area (%)	60	60	65	65	60	60	50	50
Consumption: office equipment (kWh/m^2)	12	18	19.5	27.3	23.1	31.2	22.5	31.5

Table 4-6 provides a summary of the typical power consumption figures provided in both versions of Guide F. Information regarding typical hours of usage were included in the 2nd edition yet these have been removed from the 3rd edition as they were based on a study carried out in the early 90s and were deemed out of date (Parsloe and Hebab, 1992).

Table 4-6: Typical levels of energy used by office equipment published in CIBSE Guide F

Item	Max. rating (W)	Average consumption (W)		Stand-by consumption (W)	
	2nd ed.	2nd ed.	3rd ed.	2nd ed.	3rd ed.
PC and monitor	300	120-175	n/a	30-100	n/a
Personal computer	100	40	65	20-30	6.6
Laptop computer	100	20	15-40	05-10	1.4-4
Monitors	200	80	30	10-15	0.52-1.54
Laser Printer	1000	90-130	110	20-30	10-20
Ink Jet Printer	800	40-80	n/a	20-30	n/a
Printer/scanner/copier	50	20	135	08-10	20-80
Photocopiers	1600	120-1000	550-1100	30-250	15-300
Fax machines	130	30-40	20-90	10	10-15
Vending machines	3000	350-700	n/a	300	n/a

Despite the recent update to Guide F, additional information to help designers generate realistic predictions of small power consumption is still lacking in the following areas:

- typical hours of usage for each equipment type;
- levels of use/stand-by; and
- typical number of equipment per m^2 or staff.

This study addresses the first two issues listed above and presents a series of small power load profiles for different types of appliances commonly found in office buildings. The monitored data was also used for comparison against the published benchmarks for typical levels of energy use (summarised in Table 4-6).

A minimum of two appliances were monitored for each equipment type, with the exception of desktop inkjet printers. Power demand was monitored at 5-minute intervals over a 2-week period and aggregated energy consumption was logged every 30 minutes (refer to Section 3.2.2.4). Table 4-7 details the scope of appliances monitored and the representation in both publications of Guide F.

Table 4-7: Description of data included in the study as well as both editions of Guide F

Item		2nd ed.	3rd ed.	Monitoring Study	Comments
Laptop Computers		✓	✓	✓	Monitoring included machines with distinctive processing powers
Personal Computers		✓	✓	✓	
Monitors		✓	✓	✓	Monitoring included a variety of screen dimensions
Printer	Laser	✓	✓	✗	Not available in the case study office building
	Ink jet	✓	✓	✓	Only one desktop inkjet printer was available for monitoring
Printer/scanner/copier		✓	✓	✗	Not available in the case study office building
Photocopiers		✓	✓	✓	Monitoring included two machines of similar specifications
Fax machine		✓	✓	✗	Not available in the case study office building
Vending machines		✓	✗	✓	Monitoring included hot and cold drinks units
Microwave oven		✗	✗	✓	Commonly found in office buildings but not included in benchmarks – worthwhile investigating
Fridge		✗	✗	✓	

4.3.3 KEY OUTCOMES

Figure 4-8 displays the results from the monitoring study compiled into graphs illustrating the typical weekday load profiles for different equipment. Table 4-8 highlights key power demand values for stand-by mode, maximum demand and average in-use demand. It is worth noting the 'maximum demand' values relate to the half hourly averages and peaks within this interval are likely to have been higher.

Figure 4-9 provides a graphical representation of the monitored data alongside the benchmarks published in both editions of Guide F. Power demand figures are illustrated as single data points or ranges in line with the available information.

Note that benchmarks for fridges and microwave ovens are not covered in either edition of Guide F so have not been included. Benchmark data for maximum demand is no longer available in the 3rd edition of Guide F, having been replaced by nameplate ratings and so comparisons for maximum demand have been made against the 2nd edition of Guide F only. Benchmarks for vending machines have also been removed in the 3rd edition of Guide F.

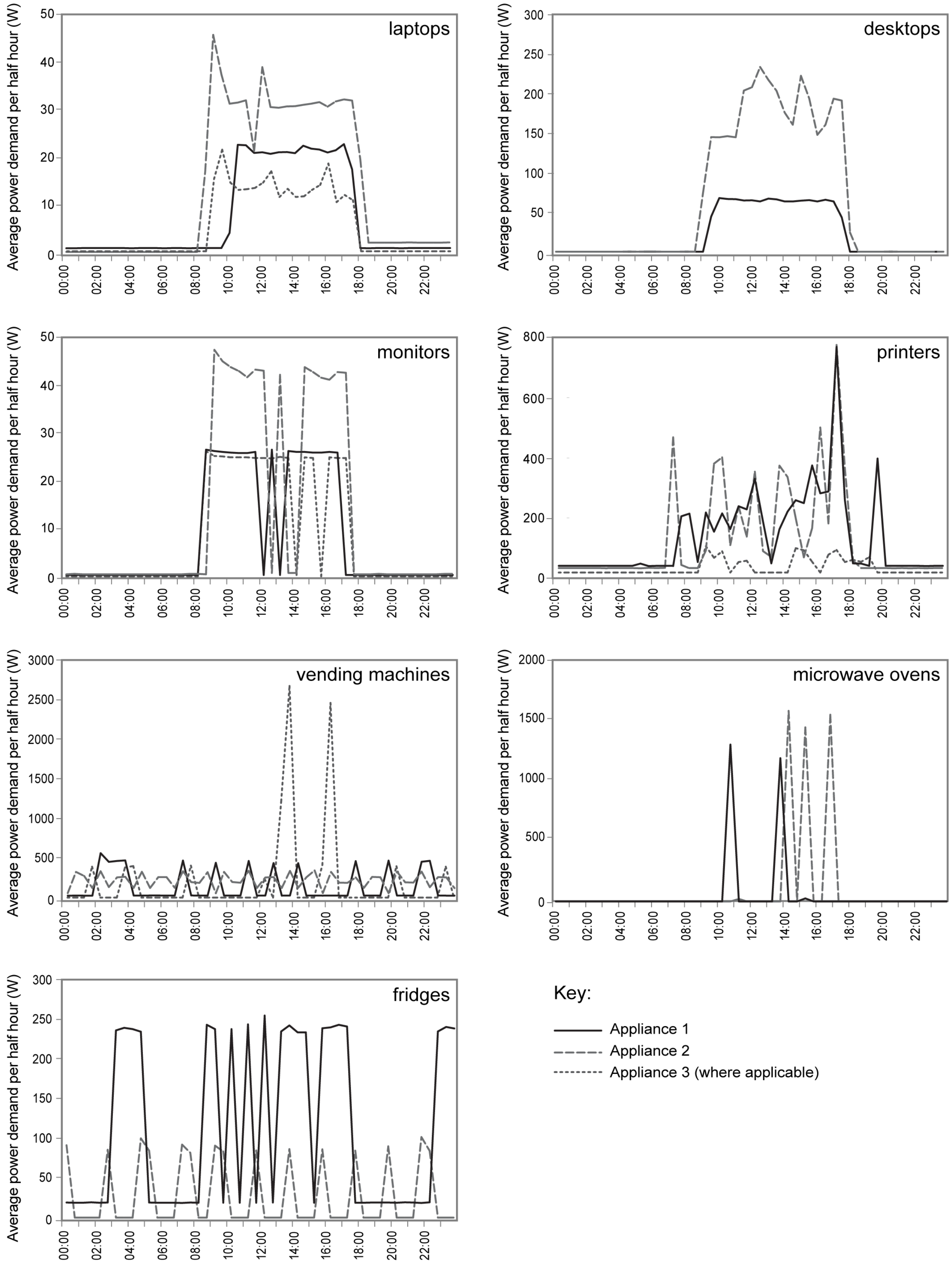

Figure 4-8: Monitored power demand profiles for each appliance

Table 4-8: Key power demand values for each monitored appliance

	Equipment	Appliance 1	Appliance 2	Appliance 3
a	Laptops	1.3 GHz Intel Centrino processor	2.3 GHz Intel Core Duo processors	2.6 GHz Intel Core i5 processors
	Stand-by mode	1.1	0.3	0.5
	Maximum demand	22.9	45.8	27.6
	Average in-use	20.3	30.9	17.9
b	Desktops	2.3 GHz Intel Core Duo processors	3.4 GHz Intel Xeon processors	-
	Stand-by mode	1.9	2.0	-
	Maximum demand	69.1	233.7	-
	Average in-use	64.1	168.6	-
c	Monitors	19” LCD flat screen	19” LCD flat screen	21” LCD flat screen
	Stand-by mode	0.7	0.4	0.8
	Maximum demand	26.7	26.3	47.7
	Average in-use	23.2	22.4	35.7
d	Printers	Large network printer/photocopier	Large network printer/photocopier	Desktop ink-jet printer
	Stand-by mode	37.2	29.9	15.6
	Maximum demand	765.1	771.6	103.0
	Average in-use	223.2	235.1	49.1
e	Vending Machines	Snacks (food)	Cold drinks	Hot drinks
	Stand-by mode	89.0	88.9	23.4
	Maximum demand	623.3	392.6	2663.9
	Average in-use	158.8	262.1	337.8
f	Microwave Ovens	800W power rating	900W power rating	-
	Stand-by mode	2.1	1.9	-
	Maximum demand	1299.7	1578.9	-
	Average in-use	115.8	210.4	-
g	Fridges	Full size fridge (375 L)	Small fridge (150 L)	-
	Stand-by mode	18.0	0.0	-
	Maximum demand	237.8	98.8	-
	Average in-use	133.6	26.4	-

Results from this study suggest that the benchmarks published in the 2nd edition of Guide F were broadly unrepresentative of small power equipment currently being used in office buildings. Key findings were:

- the monitored desktop computers have higher maximum and average demands than the CIBSE Guide F 2nd edition benchmarks;
- laptop computers were observed to have lower maximum demands than the 2nd edition benchmarks, although average consumption values were reasonable;
- stand-by power demand for both laptop and desktop computers were observed to be only a fraction of the 2nd edition benchmarks;
- 2nd edition benchmarks for computer monitors relate to CRT monitors, being unrepresentative of energy consumption by LCD monitors which are widely used in contemporary office buildings;
- benchmarks for printers and photocopiers were fairly representative, accepting that the machine workload is not accounted for in the benchmarks, or in the study;
- refrigerating vending machines were fairly well represented, however machines that supply heating on demand can consume significantly more energy and are heavily workload dependant, something that is not addressed in the Guide.

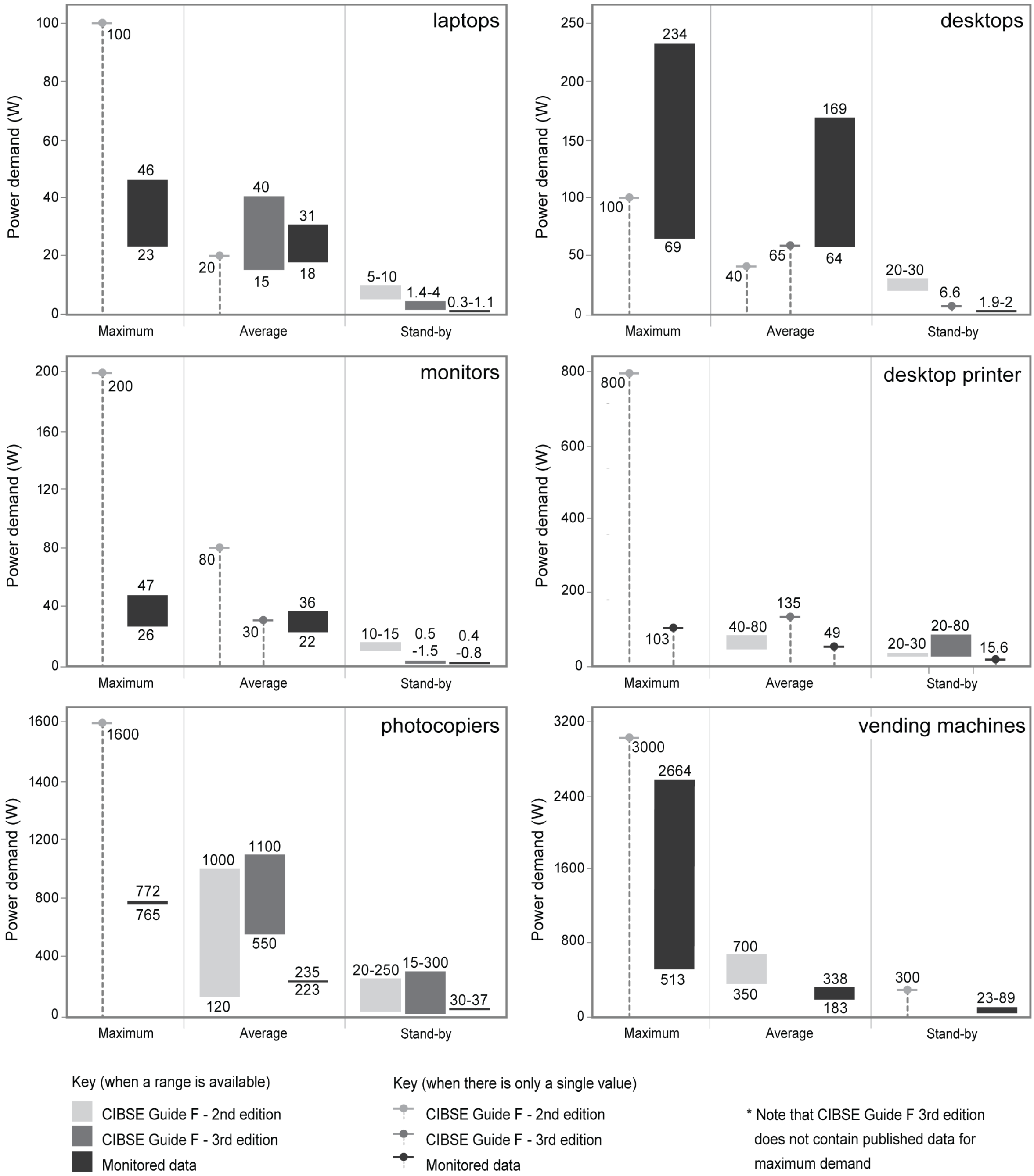

Figure 4-9: Comparison of benchmarks and monitored power demand for small power equipment

A review of the recently published 3rd edition of CIBSE Guide F demonstrated that the updated benchmarks were generally more representative of the monitored equipment, however there were some notable observations:

- the average demand for high specification desktop computers can be significantly larger than the benchmarks suggest and hence an understanding of this equipment is critical when estimating operational energy consumption;
- photocopiers required a measure of expected load if reasonable estimates are to be derived from the benchmarks;
- in all cases it would appear that the standby loads are over estimated in the new Guide, accepting that the limitations of this study may bias the results presented.

4.3.4 SUMMARY

The revised Guide F is a significant step forward, offering more appropriate guidance on expected appliance consumption. However there is still work to be done to inform designers on how to better predict small power loads in-use, through the development of metrics that give an indication of typical hours of use or appliance workload. A stronger dialogue between designers and clients is also of utmost importance so that equipment specifications and operational characteristics can be accurately established, allowing designers to make better estimates of small power energy consumption in-use.

Overall this study has emphasised the need for up-to-date benchmarks so that small power equipment can be appropriately accounted for in predictions of energy consumption as well as power demand (and subsequent heat gains). The study has also demonstrated that power demand can vary significantly amongst the different equipment classed under the same benchmark category (such as desktop computers). It has also highlighted the importance of considering the different operational modes of each equipment type, providing typical usage profiles to illustrate likely operational patterns. There is scope however, to investigate the variability of usage profiles and operational patterns, as these are likely to vary with different users.

4.4 STUDY 4: ASSESSING THE IMPACT OF OCCUPANT BEHAVIOUR ON MONITORED ELECTRICITY CONSUMPTION

The fourth study undertaken as part of this EngD addresses Objective 4 of this thesis: "Investigate the contributing factors to variations in small power energy consumption". Preliminary findings of the research suggested that occupant behaviour was a key contributing factor to small power energy consumption. This study provides an initial investigation into the impact of occupant behaviour on variations of energy use by different tenants occupying the same building.

4.4.1 SCOPE AND AIMS

This study was presented at the Seventh International Conference on Innovation in Architecture, Engineering and Construction (refer to 0) and focuses on the impact of occupant behaviour on the electricity consumption for lighting and small power in a multi-tenanted office building. The study is based on the principles of the Theory of Planned Behaviour (refer to Section 2.2.3) and was conducted in collaboration with a fellow EngD candidate sponsored by AECOM (R. Tetlow). The main aims of the study were to:

- develop a methodology for quantifying the impact of occupant behaviour on variations in electricity consumption for lighting and small power;
- assess the impact of different precursors to behaviour on the variation of electricity consumption in different zones of the building.

The development and implementation of the study was lead by the researcher with support from R. Tetlow (and his supervisors). The analysis of the data including linear and multiple regression analysis was undertaken by R. Tetlow.

4.4.2 OVERVIEW OF THE STUDY

This study was undertaken in an 8-storey multi-tenanted office building located in Central London (refer to Building 1 in Section 4.1.2 for more details). Two distinctive sets of data were acquired for each of the 32 sub-metered zones in the building: one pertaining to the use of electricity for lighting and small power; the other regarding occupant behaviour.

Monthly electricity consumption data for lighting and small power was acquired through the existing metering configuration of the building. Out of the 32 data points (i.e. sub-metered zones) only 27 of them were deemed appropriate for inclusion in the study, as 2 zones were unoccupied and 3 zones were reception areas consisting mainly of transitional spaces.

A questionnaire was developed in line with guidance by Francis et al. (2004) aiming to assess occupant behaviour in each building zone (as detailed in Section 3.2.3). The questionnaires were distributed to all occupants in the building (approximately 800 people) between 8am and 10am on 1st November 2011. Respondents were informed that the questionnaires would be collected after 3pm on the same day. Care was taken to annotate each questionnaire with the zone in which the respondent was seated. A total of 432 completed questionnaires were collected, representing a response rate of approximately 50%. Scores for each of the three predictors were calculated for each respondent as follows:

$$Behavioural\ attitude\ score = \sum_{i=1}^{i=6}(behavioural\ belief_i \times outcome\ evaluation_i)$$

$$Subjective\ norm\ score = \sum_{i=1}^{i=6}(normative\ belief_i \times motivation\ to\ comply_i)$$

$$Perceived\ behavioural\ control\ score = \sum_{i=1}^{i=6}(control\ strength_i \times control\ power_i)$$

A median score for each predictor was then calculated for all 27 building zones included in the study.

4.4.3 KEY OUTCOMES

Figure 4-10 illustrates the correlation between monitored monthly electricity consumption and the median scores of the occupants of each zone on each of the three predictors of the Theory of Planned Behaviour.

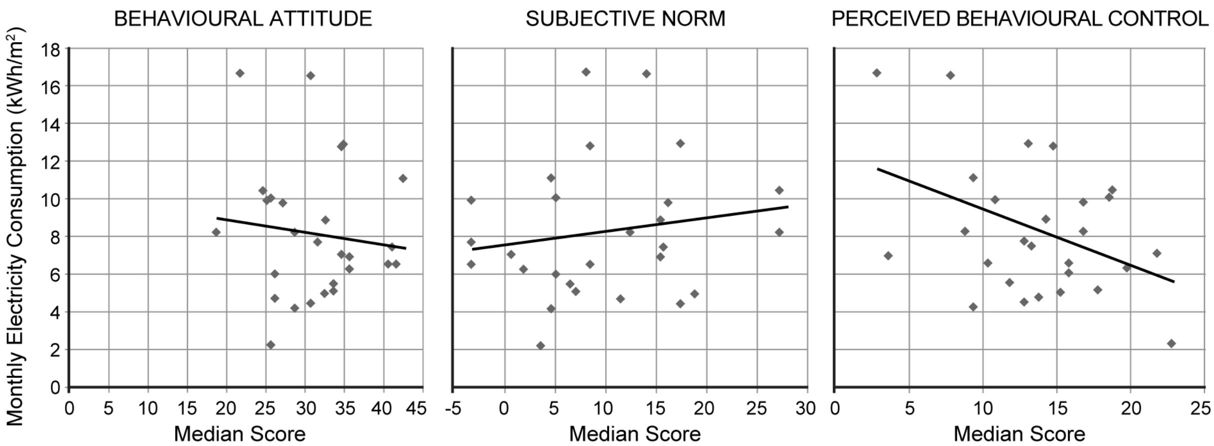

Figure 4-10: Scatter plots of electricity consumption vs. median scores

A multiple regression analysis was undertaken (by R. Tetlow), revealing that perceived behavioural control is the only predictor that has a statistically significant impact on electricity consumption. This implies that, in the building under investigation, lower electricity consumption could be expected in zones where occupants perceive themselves to have a high level of control over lighting and appliances. No correlation was found between either behavioural attitude or subjective norms, and monitored electricity consumption for the zones. Using a linear regression analysis with perceived behavioural control as the sole predictor of monthly electricity consumption revealed that it accounts for approximately 17% of the variation in monthly electricity consumption.

The structure of the TPB goes some way towards explaining these findings as it proposes a direct link between perceived behavioural control and behaviour, whereas the other predictors are linked only to intention. It is important to emphasise that TPB only considers planned behaviour, so for the purposes of this study it can only be used to explain the variation in electricity consumption caused by the conscious operation of lighting and appliances. The intangible nature of electricity use renders it likely that a certain proportion of electricity consumption in buildings is a result of unplanned or instinctive behaviour which will not be accounted for by TPB, as well as other important factors out of the occupants' control (such as workstation density, occupancy hours, procurement of appliances and light fittings, etc).

4.4.4 SUMMARY

Results from the study demonstrated a statistically significant, negative association between scores for perceived behavioural control and electricity consumption, suggesting that perceived lack of behavioural control can account for variations of up to 17% in electricity consumption in each of the building zones. According to the TPB, perceived behavioural control can often be used as a substitute for a measure of actual control and is of greater psychological interest, following the premise that people's behaviour is strongly influenced by their confidence in their ability to perform it (Azjen, 1991). The findings from this study substantiate this claim, illustrating that the more control people perceive to have over their surroundings, the less energy they consume. This premise goes against the current design trend for more automated buildings.

Although the results from this study provide an insight into the impact of occupant behaviour, it did not provide a usable outcome for modelling the impact of occupants on small power electricity consumption. The fact that individual behavioural scores had to be averaged out to represent an entire building zone may have been a significant limiting factor in this approach. Restrictions in acquiring separate lighting and small power energy consumption data might also be a key contributor to the study's shortcoming. Further application of this methodology would require sub-metered data for small power alone as well as a significantly larger sample of different tenants. These factors prevented further investigations to be carried out using the TPB. Consequently, alternative methods for investigating the impact of occupant behaviour on small power consumption should be considered and applied in subsequent studies. These should allow for energy use metrics at the equipment level to better account for the variations in the behaviour of individual users rather than an entire building zone.

4.5 STUDY 5: EVALUATING THE ELECTRICITY CONSUMPTION AND USAGE PATTERNS OF LAPTOP AND DESKTOP COMPUTERS

The fifth study undertaken as part of this EngD further addresses Objective 4 of this thesis: "Investigate the contributing factors to variations in small power energy consumption". Findings from Study 4 suggested that one aspect of occupant behaviour had a statistically significant impact on variations of electricity consumption in different zones in a multi-tenanted office building. This study further investigates the impact of occupants on variations of energy use at the equipment level (rather than at high level, sub-metered electricity consumption). This was undertaken through detailed power demand monitoring of different combinations of computers and users.

4.5.1 SCOPE AND AIMS

This study provides an analysis of small power energy consumption and usage patterns of computers in two UK office buildings. The main aims of the study were to:

- provide insight into the use of computers in contemporary offices;
- investigate the key factors influencing energy consumption of computers;
- inform the development of a tool for estimating electricity consumption and power demand of small power equipment.

4.5.2 OVERVIEW OF THE STUDY

Energy consumption is a product of power demand and time. Broadly, power demand in each operational mode is dictated by the specifications of the equipment and the time spent on each mode is mainly influenced by the user. However there are deeper and more complex relationships between both of these factors. The user will establish what activities are to be performed by the equipment, impacting on the operational mode of the machine and in turn influencing power demand. Meanwhile, the equipment's specification will determine how much time it takes to perform a given task, influencing the time spent on different operational modes. Results detailed in Section 4.1 suggest that the organisational practices and working policies can have a significant impact on energy consumption. Moreover, the organisation is usually responsible for procuring office equipment, influencing the specification and range of power demand by the equipment, also establishing the job requirements and working practices to which the user must comply. These relationships are illustrated in Figure 4-11.

A total of 8 laptop computers and 5 desktop computers were monitored over a two-month period at a sample rate of one minute using plug monitors (refer to Section 3.2.2.4). Table 4-9 contains a summary of the computers monitored as part of the study. The sample of users represents a variety of job roles yet they are all employed by the same company. The computers were categorised into high-end, medium and low-end based on the range of laptops and desktops procured by the company. A series of 'window-plots' were developed for each monitored computer (as described in Section 3.2.4).

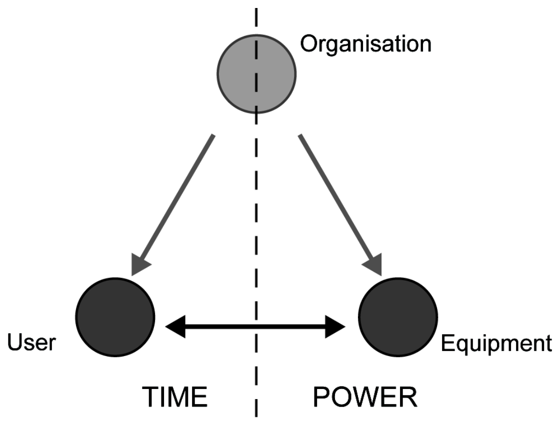

Figure 4-11: Influencing factors on small power energy consumption

Table 4-9: Details of the computers monitored as part of the study

	Computer	Specification	Processor (GHz)	Memory (GB)	User	Year of manufacture
L1	Laptop 1	High-end	2.6	4.0	Regional director	2011
L2	Laptop 2	High-end	2.6	4.0	Regional director	2011
L3	Laptop 3	High-end	2.6	4.0	Senior consultant	2011
L4	Laptop 4	High-end	2.6	4.0	Engineer	2011
L5	Laptop 5	Medium	2.2	2.0	Associate director	2008
L6	Laptop 6	Medium	2.4	2.0	Principal consultant	2008
L7	Laptop 7	Low-end	1.6	2.0	Consultant	2008
L8	Laptop 8	Low-end	1.6	2.0	Graduate consultant	2008
D1	Desktop 1	High-end	4.8	4.0	Architect	2010
D2	Desktop 2	High-end	4.8	4.0	Senior designer	2010
D3	Desktop 3	Medium	4.4	4.0	Landscape architect	2010
D4	Desktop 4	Low-end	3.4	4.0	Admin staff	2011
D5	Desktop 5	Low-end	3.4	4.0	Admin staff	2011

4.5.3 KEY OUTCOMES

Figure 4-12 illustrates the proportion of typical to atypical days for each computer/user, highlighting significant variations. Users with the highest percentage of atypical days were generally in senior roles, such as L1 and L3, often being out of the office, as well as users who left their machines running overnight, such as D1 and D2. Most desktop users left their computers on to perform time-consuming tasks such as energy models and renders, yet D4's job role did not include such tasks. Discussions with D4 revealed that they did so to save time starting up the following day.

Figure 4-13 illustrates the mean, maximum and minimum daily energy consumption for each computer. The plots on the left illustrate the values calculated for typical days whilst the plots on the right illustrate the values for all monitored days.

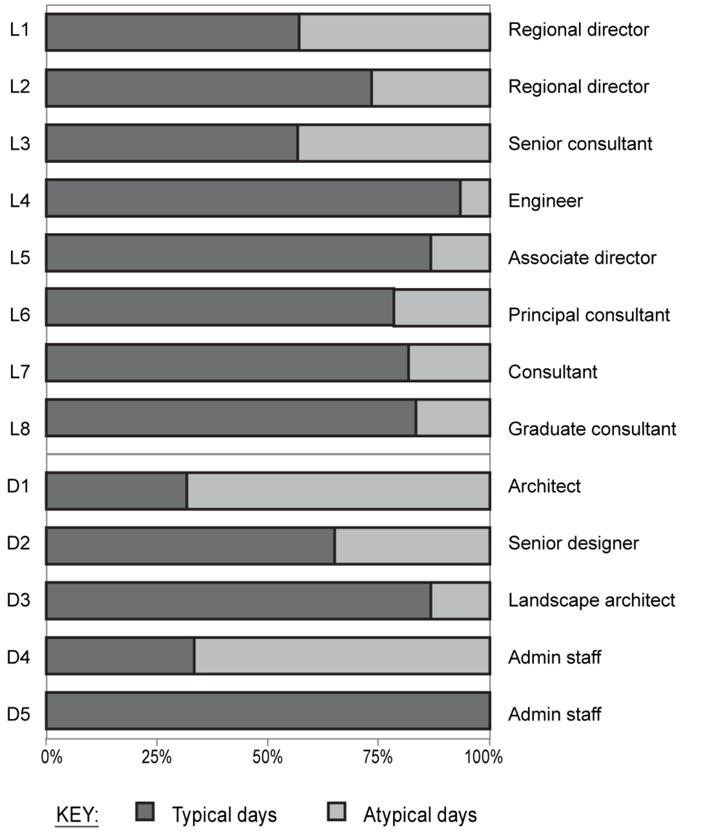

Figure 4-12: Proportion of typical and atypical days monitored for each computer

For laptops, the ranges of daily consumptions were observed to be lower on atypical days than typical days. The opposite occurred for desktop users, where higher daily consumptions are recorded on atypical days, highlighting the previously discussed usage patterns. The newer, high-end laptops were observed to have generally lower daily consumptions values than the medium and low-end laptops, emphasising the premise that laptop computers are getting more efficient. Daily consumption ranges for desktops suggest that higher processing power results in significantly higher energy consumption.

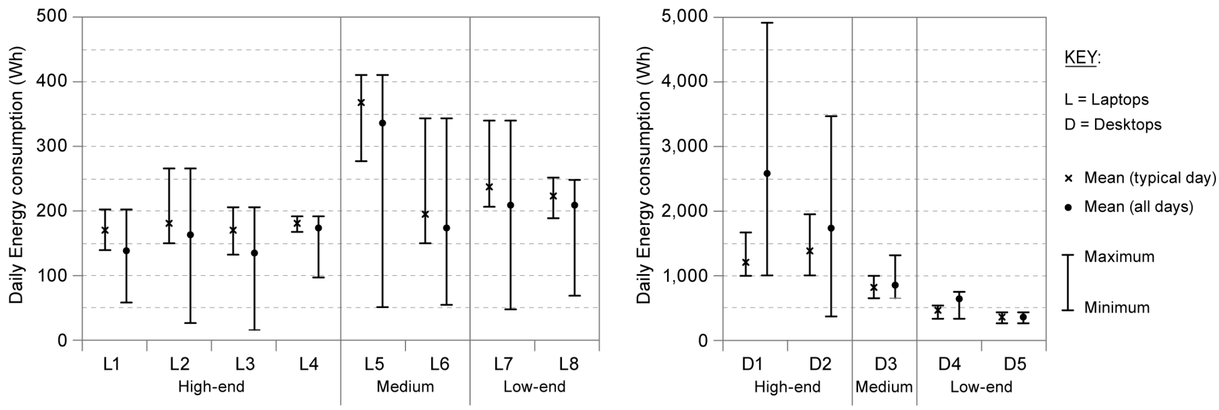

Figure 4-13: Mean, maximum and minimum daily consumption monitored for each computer on typical and atypical days

Figure 4-14 and Figure 4-15 illustrate the window-plots depicting the mean power demand and time spent on each operational mode (alongside their respective uncertainties) for each monitored desktop and laptop computer (respectively). These plots provide a practical approach for visualising and comparing the relationships depicted in Figure 4-11 whilst also highlighting the differences in operational patterns.

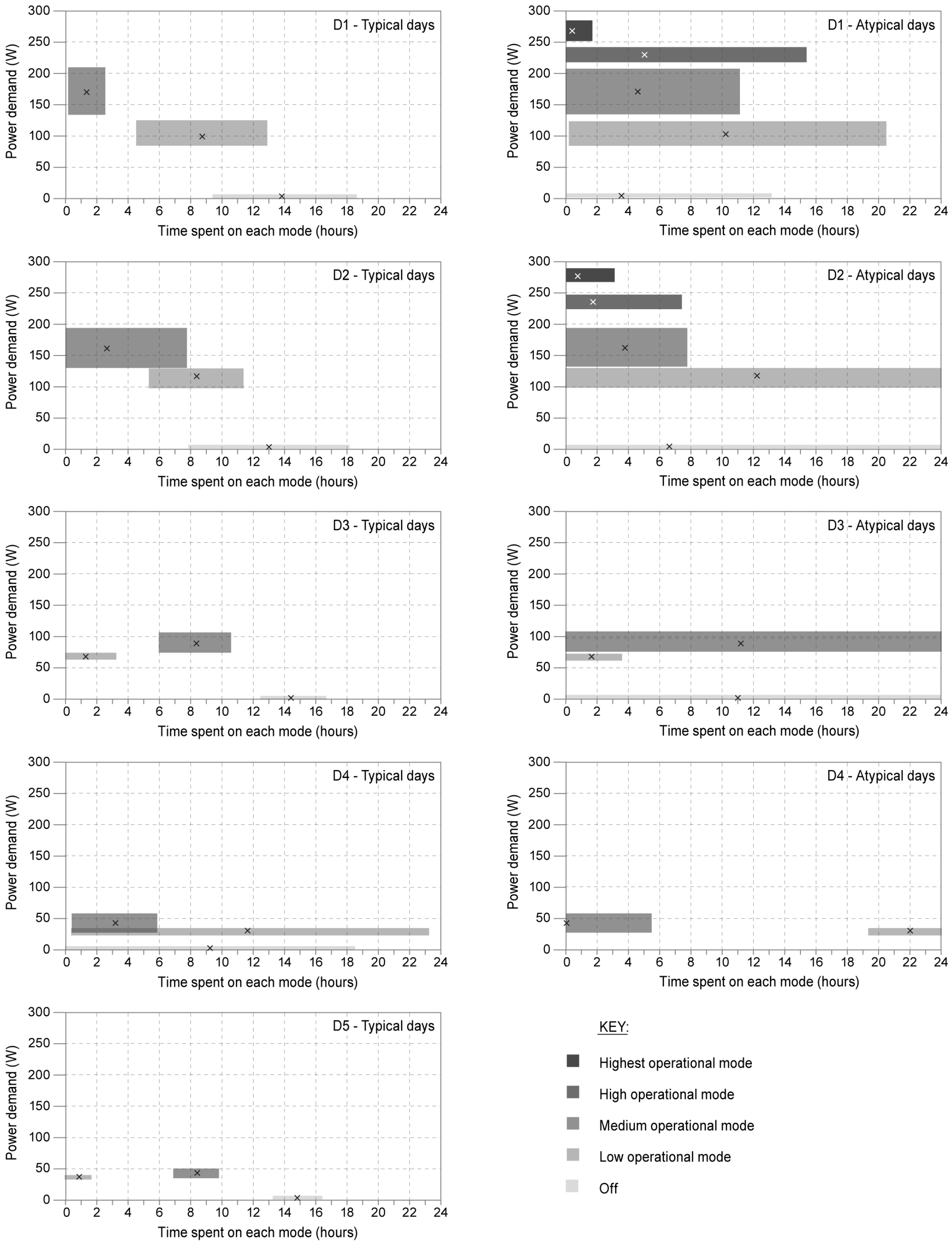

Figure 4-14: 'Window-plots' illustrating the mean power demand and time spent on each operational mode for the monitored desktop computers.

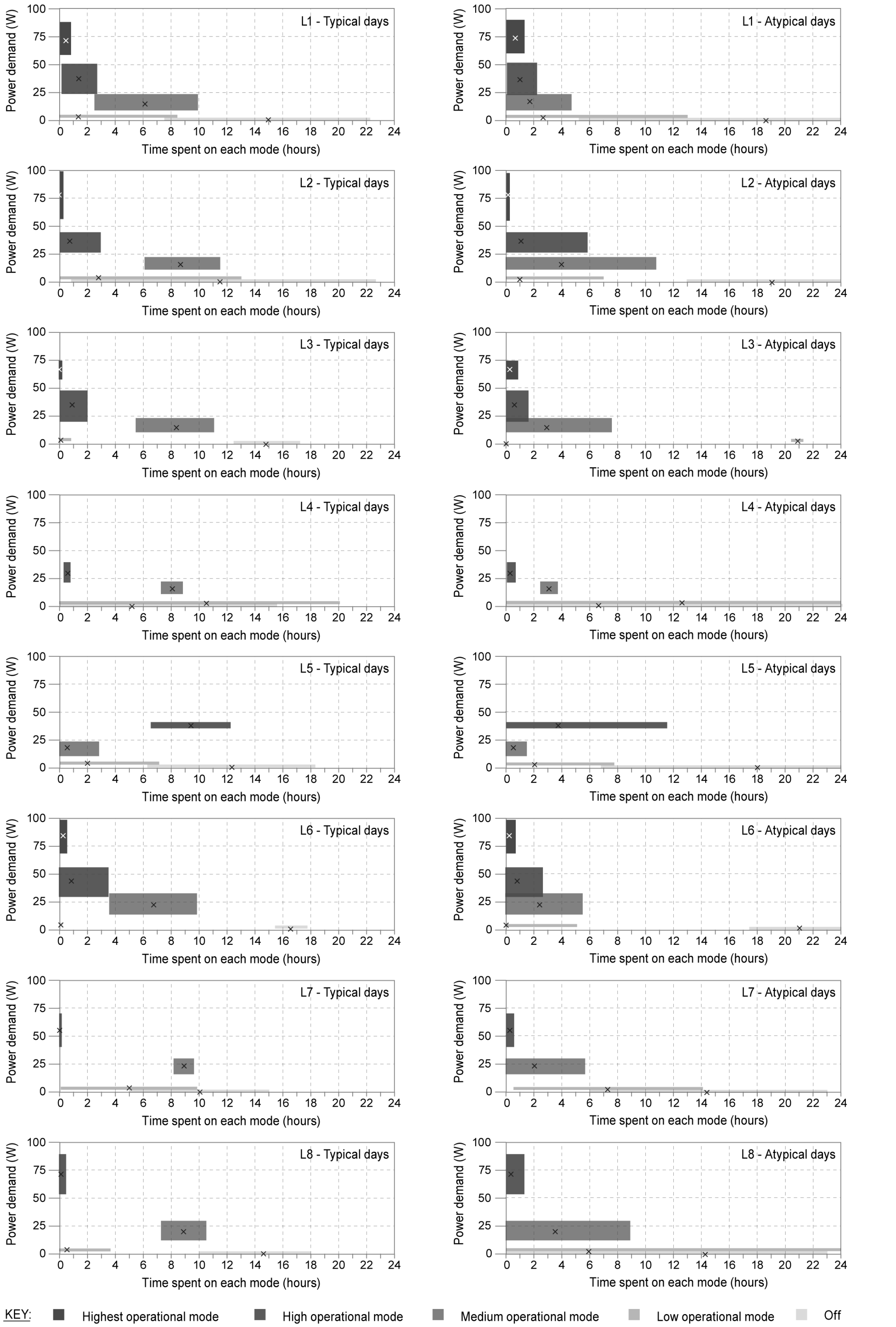

Figure 4-15: 'Window-plots' illustrating the mean power demand and time spent on each operational mode for the monitored laptop computers.

Focusing on the higher operating modes (medium, high and highest) the window-plots suggest that the higher the mode, the less time is likely to be spent on it. Exceptions include L5 and D3, whose highest operating modes are predominantly the one in which most time is spent. This would suggest that both L5 and D3 users are performing tasks that consistently demand the most out of their machines. Comparing the window-plots for L5 and L6 to their respective daily consumptions (Figure 4-13) reveals that although L5 has a significantly lower maximum demand than L6, it has higher maximum and mean daily consumption values. This would suggest that energy savings could be made by replacing L5 with a higher specification computer (given the same user and job requirements).

Power demand values for 'off' and 'low' modes are very similar for laptop computers suggesting that 'low' represents the formal 'sleep' mode whilst also highlighting the power demand trends discussed in the literature review. The mean time spent on 'low' and 'off' modes are observed to vary significantly resulting in wide prediction intervals for most laptops. Time spent 'off' represents the operational mode where the greatest number of hours is spent for all laptops except L4 who often leaves his/her computer operational overnight.

Focusing on desktop computers, the highest operating modes only occur on the atypical days and significant uncertainties are recorded for the high operating mode on both high-end desktop computers. The medium desktop (D3) presented similar operational patterns to L5 whereby most of the operational time was spent on the on the highest mode of operation. Meanwhile, the window-plots for the low-end desktops clearly illustrate the impact of the users' attitudes: although both users have the same job role, D4 is consistently left on overnight, whereas D5 is diligently switched off at the end of each working day.

Table 4-10 and Table 4-11 provide a summary of the mean time each computer spent 'on' and 'off' per day as well as an overall mean for all the monitored laptops and desktops. As seen, the monitored laptop computers have a mean 'on' time of 10.9 hours, whilst desktops have an even higher mean at 14.1 hours. Data published by Kawamoto et al. (2004) suggests that PCs (laptops and desktops) are on for an average of 6.9 hours per day, based on the monitoring of 7 computers in conjunction with a survey of 145 office workers. Comparing both sets of results would suggest that computers are currently used for longer periods of time. This could be a result of different working practices amongst the office buildings investigated in each study but could also be a reflection of more general changes to the working environment over the last decade.

Results from Moorefield (2011) suggest that desktops and laptops are switched off for only 1.7 hours and 6.2 hours a day on average (respectively), highlighting even longer usage periods. Overall, both data sets illustrate that desktop computers are likely to be operated for longer periods of time than laptop computers. Results also emphasize that significant variations occur on the operational patterns of computers, even amongst studies undertaken in recent years. This is likely to be influenced not only by working practices but also by user behaviours.

Table 4-10: Mean time spent on and off by laptops

	Mean time 'ON' (hours/day)	Mean time 'OFF' (hours/day)
L1	7.5	16.5
L2	13.7	10.3
L3	7.2	16.9
L4	18.9	5.1
L5	10.9	13.0
L6	6.7	17.3
L7	13.0	10.9
L8	9.4	14.6
Mean	**10.9**	**13.1**

Table 4-11: Mean time spent on and off by desktops

	Mean time 'ON' (hours/day)	Mean time 'OFF' (hours/day)
D1	17.1	6.9
D2	13.3	10.7
D3	10.0	14.0
D4	21.0	3.1
D5	9.1	14.9
Mean	**14.1**	**9.9**

Figure 4-16 illustrates the probability of each individual laptop and desktop computer being switched on throughout all monitored days. The darkest line illustrates the mean probability for all desktop and laptops demonstrating that in general, desktops have a larger probability of being on overnight, approximately 0.3 compared 0.1 for laptop computers. The mean plots also demonstrate a probability of 1 for most of the typical working hours for desktops, compared to more fluctuating probabilities for laptops, generally below 0.8 throughout typical working hours. Probability plots for individual laptops also demonstrate a significant variation in turning on / turning off times, unlike very consistent operating hours for the monitored desktops.

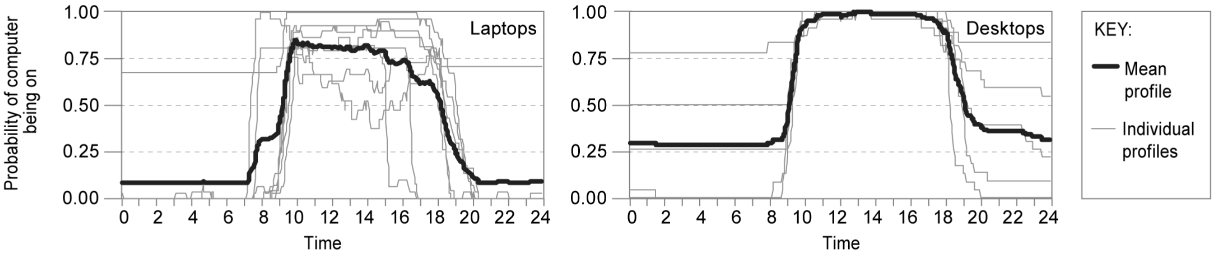

Figure 4-16: Probability of computers being 'on' at different times of the day

These results highlight the previous discussion surrounding higher out-of-hours use of desktop computers when compared to laptops. It also suggested more unpredictable usage patterns for laptop users, which can be attributed to greater flexibility in working practices provided by laptop computers alongside more stringent power management capabilities.

4.5.4 SUMMARY

Figure 4-17 summarises the conclusions drawn regarding the relationships between the users, equipment and the organisation. Although the organisation was consistent amongst all monitored computers and users, it was observed to influence two key aspects: the job requirements and computer specification. Results from the study suggest that specifying a computer that can adequately cope with the job requirements can result in energy savings (even if these have a higher peak demand). Equipment specification was seen to influence more than just power levels, influencing the probability that the computer will be switched off at the end of the day. However, that decision is ultimately down to the user, and attitudes were observed to play a larger part in such decisions than job requirements alone. Users in the same job role using the same equipment were observed to have different energy consumption levels and usage profiles.

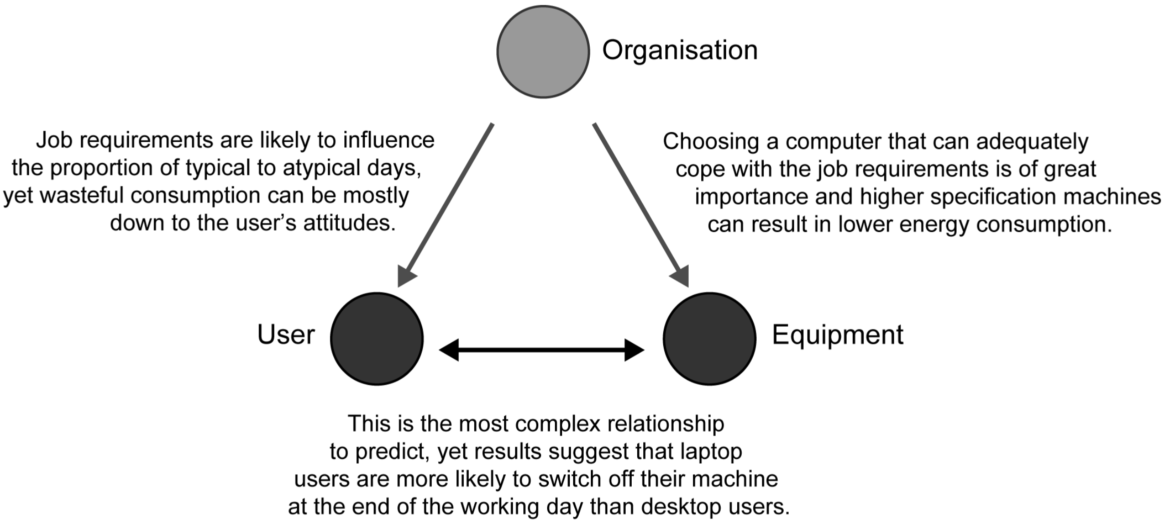

Figure 4-17: Key findings regarding the relationship between the user, equipment and organization in relation to the energy consumption of computers.

Monitored data demonstrates a significant level of variability in power demand, usage profiles and resultant energy consumption. Calculated uncertainties based on the measured values highlight the challenge in accurately predicting power demand, as well as the resultant internal heat gains. Results suggest that in order to realistically predict the power demand and energy consumption of computers, detailed information regarding the specification of the equipment would be required as well as information about the users. More broadly, results also suggest that desktop users are more likely to leave computers operational outside typical working hours than laptop users, and desktops also have a higher probability of being on during the working day.

Although this study has investigated only a small sample of computers, findings reflect real operation and usage patterns, providing insightful information on the complex factors influencing the energy consumption of computers. With the fast paced changes to the work environment, the results and discussions presented in this study provide a better current understanding of computer usage in offices. This in turn will allow for better-informed predictions to be made regarding the likely energy consumption and internal heat gains associated with computers.

4.6 STUDY 6: ESTIMATING POWER DEMAND AND ELECTRICITY CONSUMPTION OF SMALL POWER EQUIPMENT

The sixth and final study undertaken as part of this EngD addresses Objective 5 of this thesis: "Develop a model to estimate energy consumption of small power equipment, providing associated predictions of power demand profiles". This section fulfils the thesis' overarching aim by demonstrating how the factors that generate variability in small power consumption can be accounted for in representative, building specific estimates of energy use. Power demand predictions are also included as part of this study and ultimately inform the estimates of energy consumption. The overarching aim of the study however, lies on the small power consumption estimates, being the main focus of the work undertaken.

4.6.1 SCOPE AND AIMS

This final study consolidates the key findings from the previous studies and details the development and validation of two models for estimating energy consumption of small power equipment. The main aims of the study were to:

- use monitored data to inform better predictions;
- allow for the key relationships and contributing factors to be accounted for;
- provide a useable tool for designers.

The final aim presents a big challenge in that the model would require minimal inputs and timely outputs to ensure its usability amongst designers. As such, two separate models were developed: (i) a model based entirely on random sampling of detailed monitored data; and (ii) a simpler bottom-up model informed by key research findings.

A zone in one of the buildings investigated in the previous study (Section 4.5) was used to illustrate the processes behind each of the models as a worked example (below). Both models were then subjected to a blind validation by testing each methodology in a different building occupied by the same organisation. The development of both models and key results from the validation exercise are included in a paper recently submitted to Energy and Buildings Journal (Appendix E).

It is worth noting that the building zones used to inform the development of models were not used in the testing or validation of the models. Model development was based on data acquired for Study 5, consisting of two office zones occupied by the sponsor company: one in St Albans and one in London. The model testing (also referred to as worked example) was based on a separate office zone/floor in the sponsor company's London offices. The model validation was carried out for a zone in the sponsor company's Bristol offices.

4.6.2 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-minute 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 4-12 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.

Table 4-12: Equipment included in the database and installed quantities for the worked example

Equipment type	Database			Quantity of installed equipment (worked example)	Percentage of installed equipment monitored
	Quantity of monitored equipment	Weekday profiles	Weekend profiles		
Laptop computer	8	512	240	99	8.1%
High-end desktop computer	3	180	78	19	15.8%
Low-end desktop computer	2	120	52	22	9.1%
19” LCD screen	2	120	52	128	1.4%
21” LCD screen	1	60	26	22	4.5%
Large photocopier	1	60	26	4	25%
Plotter	1	60	26	1	100%
Coffee machine	2	40	16	2	100%
Fridge	1	20	8	2	50%

Monitoring took place over 3 months at 1-minute sample rates and equipment with similar specifications were grouped together to increase the sample size (within the given monitoring period length). According to Lanzisera et al. (2013) sampling faster than 1-minute does not provide significant benefit and that monitoring periods longer than a few months provide little improvement in estimating annual energy use. 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.

4.6.2.1 Calculation methodology

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 180 available in the database. This process was repeated 30 times in order to assess the variability of the data, allowing for prediction limits to be calculated (as described in Section 3.2.4.5).

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).

4.6.2.2 Comparison Against Monitored Data

Figure 4-18 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-minute intervals, metered data is illustrated in 15-minute intervals, as that is the highest resolution available with the AMR system. The metered profiles fall within the predicted range before 8am and after 8pm (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 (1-minute vs. 15-minute intervals) 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-minute 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.

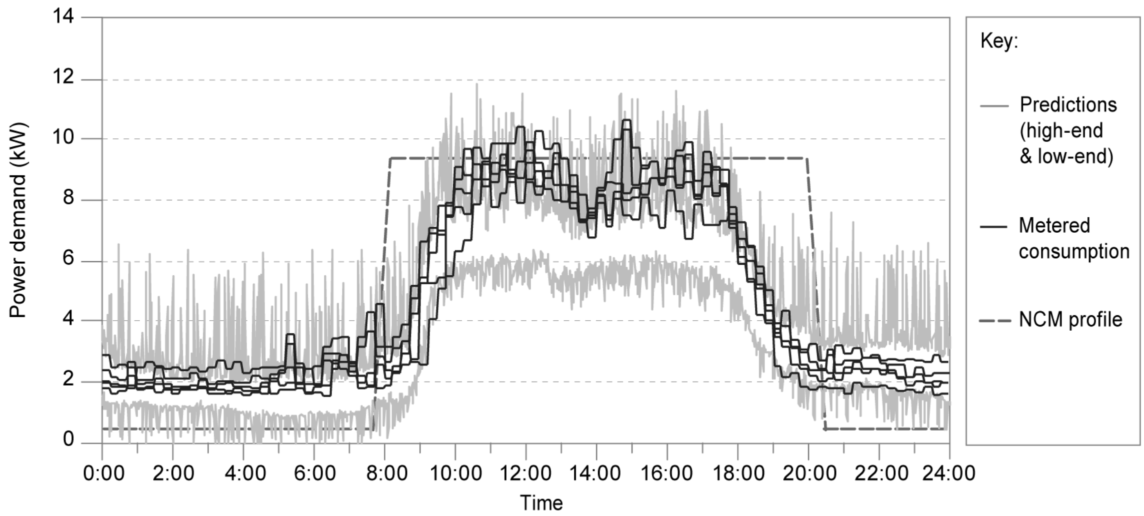

Figure 4-18: Predictions and metered weekday power demand profiles for the worked example using Model 1

Figure 4-19 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 falls in the higher end of prediction range (with the exception of December).

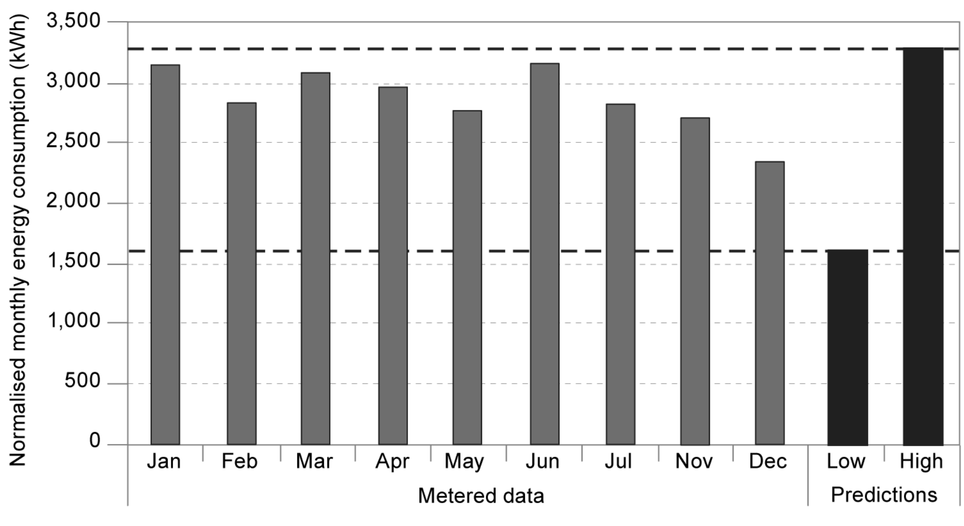

Figure 4-19: Predictions and metered monthly energy consumption for the worked example using Model 1

4.6.3 MODEL 2: BOTTOM-UP MODEL

The second model addresses the needs of industry more closely, taking a simple bottom-up approach inspired by the methodology set out in CIBSE Guide F. It is informed by findings from the previous studies 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.

4.6.3.1 Equipment Inputs

The first set of inputs relate to the types and quantities of equipment procured or installed in the area under investigation. The power demand of each equipment type is characterised into three operational modes: ‘off’, ‘low’ and ‘on’.

- P_{off} is the lowest power draw whilst the equipment is connected to the mains.
- P_{low} is defined as a low power mode that the computer is capable of entering automatically after a period of inactive.
- P_{on} represents the average power demand for all the different operational modes whilst the machine is active.

According to Wilkins and Hosni (2011), two modes of operation (active and low) are appropriate for the purpose of load calculations. 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 proportion of time on idle whilst operational (EPA, 2012). 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 (Energy Star, 2013). 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 ‘Efergy energy monitoring socket’ (with accuracy within 2%) are widely available and can provide live readings of power demand (Efergy, 2013).

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 the 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.

The profiles were established based on findings from Study 5 (Section 4.5). 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 4-13 details the equipment inputs used for the worked example based on a walkthrough audit of the installed equipment alongside findings from the study in Section 4.5.

Table 4-13: Equipment inputs for Model 2

Equipment type	Quantities		Power Draw (W)			Usage Profiles (% time)			
	Absolute	(%)	Off	Low active	On (average)	Transient	Strict Hours	Extended Hours	Always On
Computers									
High-end desktops	19	(14%)	1	80	150	15%	30%	30%	25%
Low-end desktops	22	(16%)	1	30	40	10%	70%	10%	10%
Laptops	99	(71%)	1	20	30	30%	30%	40%	0%
Screens									
19" LCD screen	128	(85%)	0	1	25	20%	50%	30%	0%
21" LCD screen	22	(15%)	0	1	45	20%	50%	30%	0%
Printers & copiers									
Photocopier	4	(80%)	30	30	220	0%	0%	100%	0%
Plotter	1	(20%)	120	120	170	0%	0%	100%	0%
Catering									
Fridge	2	(50%)	0	100	120	0%	0%	0%	100%
Coffee Machine	2	(50%)	25	25	350	0%	0%	0%	100%

4.6.3.2 Operational & Benchmarking 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). A prompt also enquires whether reduced occupancy is expected during lunchtime and if so, when this is likely to occur. Table 4-14 illustrates the operational and benchmarking inputs used to characterise the office space under investigation.

Table 4-14: Operational inputs for Model 2

Usage diversity (weekday)	75%
Usage diversity (weekend)	15%
Tarr (norm)	09:00
Tdep (norm)	17:00
Tarr (ext)	08:00
Tdep (ext)	19:00
% of computers switched off at the end of the day	60%
Reduced occupancy at lunchtime?	yes
Start time	12:00
End time	13:00

Wilkins and Hosni (2011) suggest that a diversity factor of 75% should be applied to computers in load calculations, with weekend usage diversity ranging from 10% to 30%. 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 (2011) demonstrate that peak diversity can vary on a daily basis, ranging by up to 20%. 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 (2011).

4.6.3.3 Usage Profiles

The operational inputs are used to adjust the usage profiles as illustrated in Figure 4-20 and Figure 4-21. P_{base} represents the base-load and is calculated based on the proportion of equipment switched off, representing a ratio between P_{off} and P_{low} accordingly. If lower occupancy levels are expected over lunch, the usage profiles for screens is modified to include a dip between the specified times. Results from Model 1 (Section 4.6.2) suggest that the cumulative power demand of screens is likely to reduce by approximately 25% at lunchtime, hence, P_{lunch} is estimated to be = P_{on} x 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.

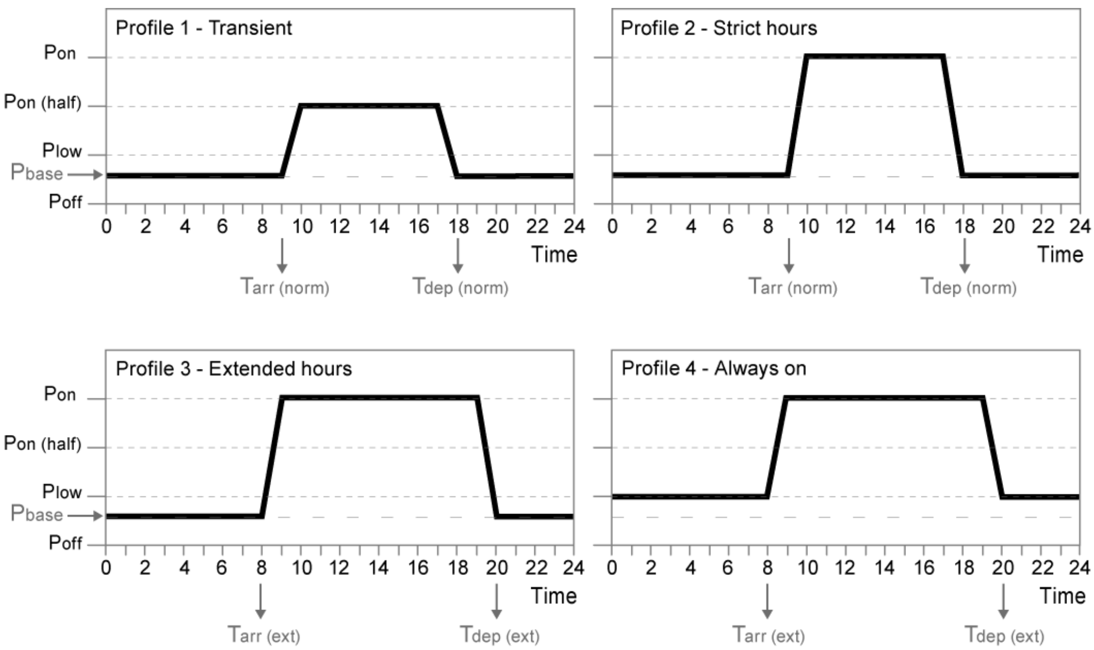

Figure 4-20: Usage profiles applied to computers in the worked example

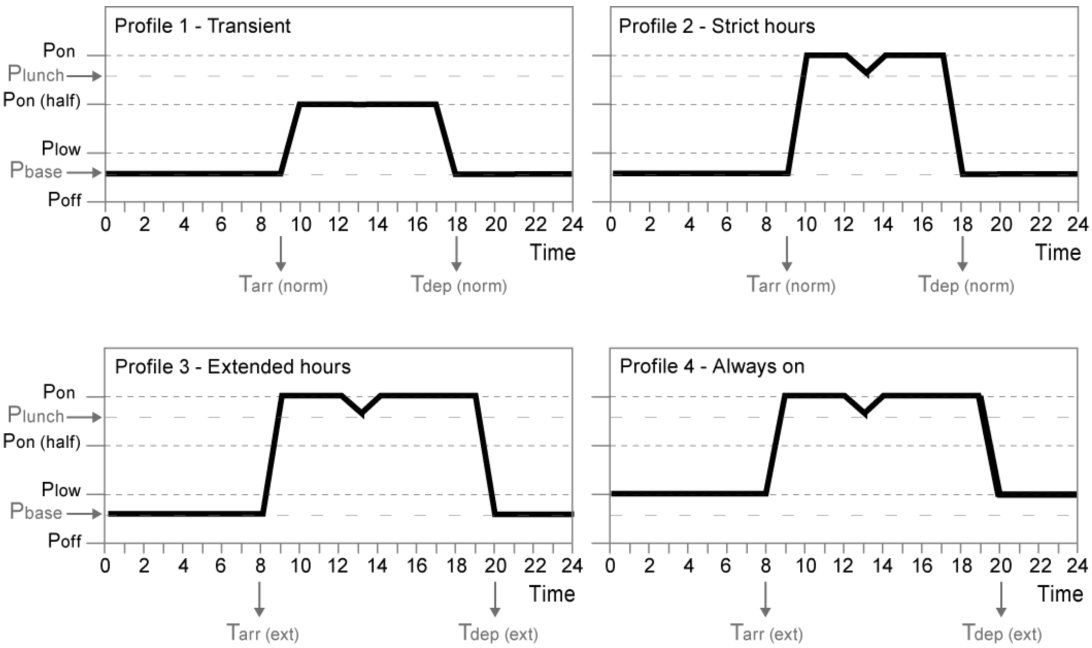

Figure 4-21: Usage profiles applied to computer screens in the worked example

4.6.3.4 Outputs

The model calculates power demand profiles in kW 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) 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.

Figure 4-22 illustrates the power demand profiles calculated by the model for the worked example. This is 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.

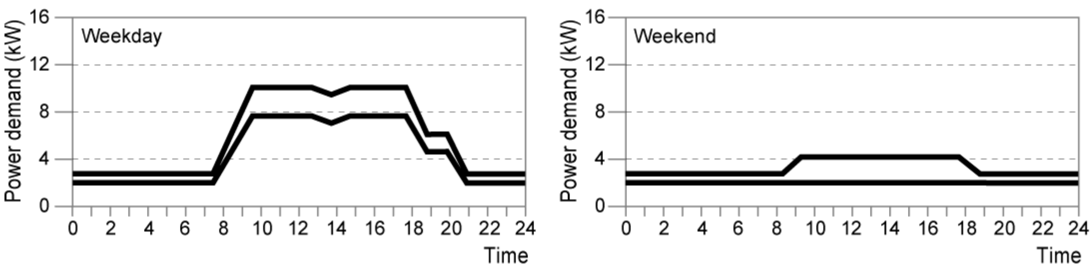

Figure 4-22: Weekday and weekend profiles for the worked example

4.6.3.5 Comparison Against Metered Data

Figure 4-23 illustrates the low-end and high-end predictions for the worked example 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 falls 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-hour intervals whereas the metered data has a frequency of 15 minutes. This discrepancy in granularity between both sets of data inherently presents a challenge to the prediction tool, yet results are still reasonable.

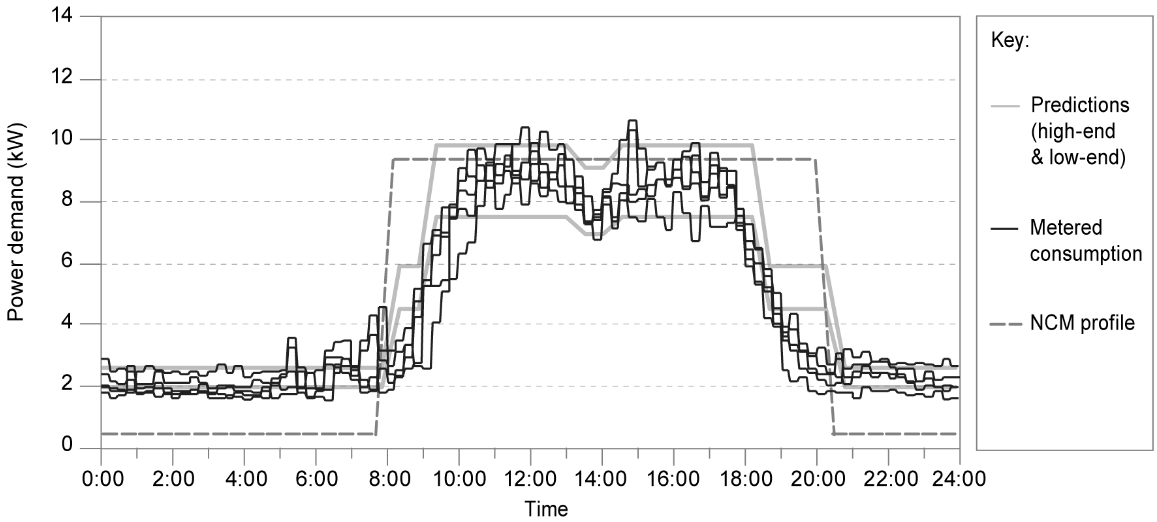

Figure 4-23: Predictions and metered weekday power demand profiles for the worked example using Model 2

Figure 4-24 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 ‘low’ prediction has been amended to represent a typical December month, including 15 working days as opposed to 20 working days.

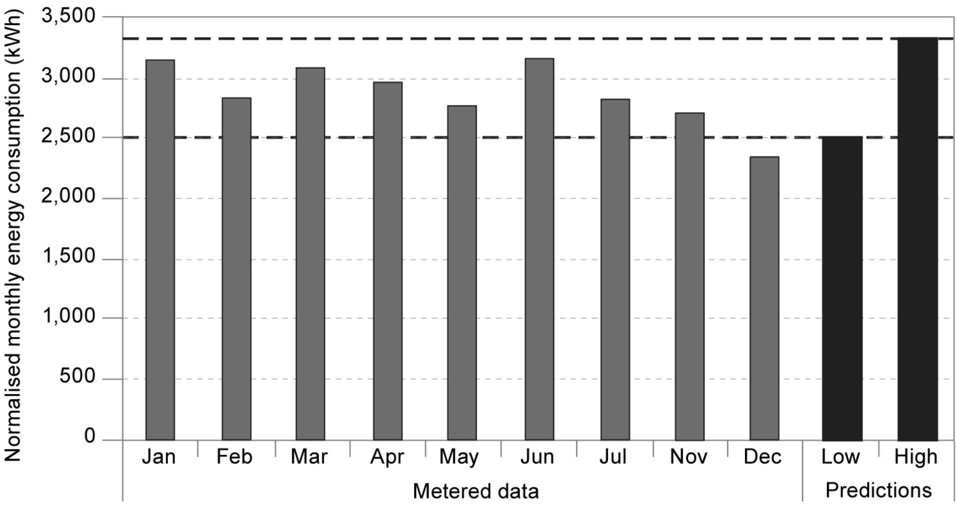

Figure 4-24: Predictions and metered monthly energy consumption for the worked example using Model 2

4.6.4 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. Monthly electricity consumption data fell entirely within the prediction range for both models. Power demand profiles were generally representative of metered data, slightly underestimating peak demand on occasion. By comparison, the NCM profile would significantly overestimate peak demand (by more than 50%) yet still underestimating overnight heat gains. A detailed description of the validation process can be found in Appendix E and key results are discussed below.

4.6.5 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 generated is to be 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-hour intervals) were still observed to be representative of metered data in intervals as small as 15-minutes. 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. Moreover, its ability to predict power demand profiles is directly related the quantity and quality of the monitored data: equipment, behaviours and operational characteristics that have not been monitored will not be accounted for in the predictions. Alternatively, the bottom-up approach (Model 2) provides a more usable tool with no detriment to the quality of predictions for energy consumption. It is worth noting however, that such a model would be used in conjunction with published benchmarks, and these must be representative of the specific equipment in-use if reliable predictions are to be made.

Figure 4-25 provides a comparison between the results from both models, metered data and benchmarks published in ECG19 (for annual energy consumption and peak power demand). 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. 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 worked example and the validation model.

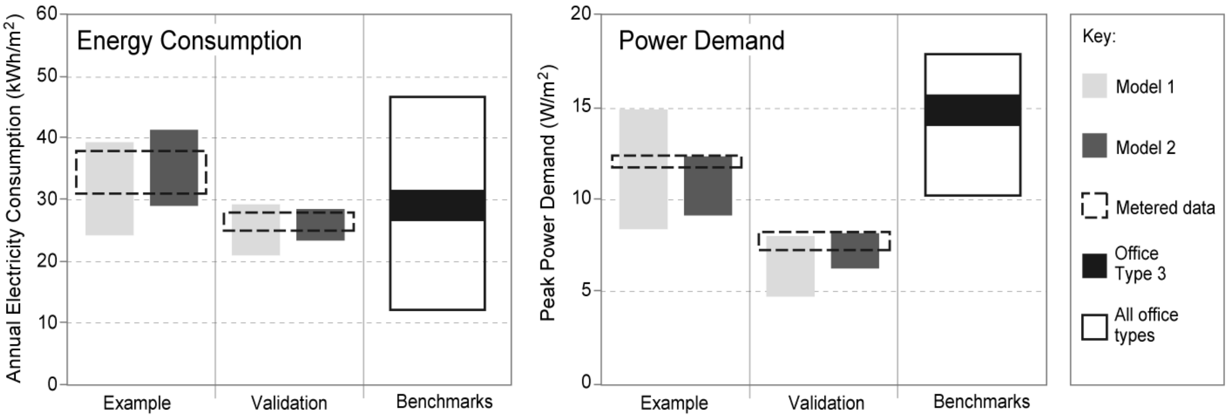

Figure 4-25: Comparison of model results against ECG19 benchmarks

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 benchmark 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. It is worth considering however, that systems are expected to last for the specified life span of the building, and allowances should be made for future developments. Both models proposed here can be used to predict the impact of operational changes to the small power loads, ensuring more resilient designs.

4.6.6 SUMMARY

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 patters 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 could benefit from additional monitoring data to inform predictions with wider applicability, yet results were observed to provide significantly better estimates than ECG 19 benchmarks. 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.

5 FINDINGS AND IMPLICATIONS

This chapter presents the main findings and implications of the work undertaken, summarising how the overarching aim and specific objectives were addressed and ultimately achieved. The contributions of the work to existing theory and practice are discussed, as well as the implications on the sponsor company and the wider industry.

5.1 KEY FINDINGS OF THE RESEARCH

The overarching aim of this EngD was to understand the factors that generate variability in small power consumption in commercial office buildings and to demonstrate how these factors should be accounted for in order to generate more representative, building specific estimates of energy consumption. This aim was achieved by undertaking six interconnected studies addressing five specific research objectives. Key findings relating to each of these objectives are summarised below.

<u>Objective 1</u>: Reviewing discrepancies between predicted and operational performance

A literature review was conducted to investigate the key factors contributing to the discrepancies between predicted and operational energy performance. This revealed that regulatory standards are heavily focused on simplified calculations undertaken at the design stage and these do not aim to predict operational energy use. The absence of numerous 'unregulated' energy end-uses from the calculations was deemed to be a key factor contributing towards the performance gap. Existing literature also highlighted the significance of a lack of information concerning the impact of occupant behaviour on energy performance of buildings. Further review of literature concerning small power equipment revealed that the fast-paced changes to the work environment are likely to influence energy consumption levels. This emphasised the need to for up-to-date benchmarks and methodologies to adequately account for small power in predictions of building operational energy performance.

<u>Objective 2:</u> Assessing the impact and variability of small power consumption

A monitoring study was conducted to assess the impact and variability of small power consumption on the operational energy performance of two multi-tenanted office buildings. Results demonstrated that there are variations in small power consumption of up to 73% amongst different tenants occupying the same building. When assessing lighting and small power consumption of the same company in two office buildings, normalised energy use was observed to be consistent, suggesting that the working practices, attitudes and behaviours of a company might transcend the immediate surroundings of the building being occupied. The study also demonstrated that computers were the single biggest energy consumer amongst small power equipment in the monitored offices.

Objective 3: Reviewing existing small power benchmarks

Investigations into current practices revealed that designers rely heavily on published benchmarks to account for small power consumption and loads at the design stage. As such, a study was undertaken to assess whether industry benchmarks are representative of equipment currently being used in office buildings. The scope of the study included benchmarks published in the 2nd edition of CIBSE Guide F, widely used by designers over the last decade, as well as recent updates published in its 3rd edition. Comparison against monitored data suggested that the benchmarks published in the 2nd edition of Guide F were broadly unrepresentative of small power equipment currently in use. The 2012 updates provided a significant improvement, offering more appropriate guidance on expected appliance consumption. However there is scope for further improvement by providing information regarding the typical hours of use and appliance workload.

Objective 4: Key contributing factors to variation in small power

The contributing factors to variations in small power energy consumption were preliminarily investigated whilst addressing Objective 2. Behavioural and management factors such as occupancy hours and the decisions surrounding the operation of computers outside of working hours were observed to have a likely influence on electricity consumption. Further evidence of the impact of hours of operation was highlighted through an investigation of the potential of using POE data to improve predictions of small power energy use. Five models were developed starting with the use of basic benchmarks and rules of thumb, progressing towards increasingly detailed estimates based on monitored data of an operational office building. Results revealed that reliable estimates can be obtained for lighting and small power loads by using realistic assumptions for installed equipment and operating hours.

The impact of occupant behaviour was analysed through two studies. The first consisted of a survey based on the Theory of Planned Behaviour and aimed to quantify the impact of individual precursors to behaviour on the variations in electricity consumption by different tenants. Limitations in sub-metering resulted in the need to assess the cumulative consumption of lighting and small power, rather than the latter alone. Results revealed that scores for perceived behavioural control had a statistically significant correlation to electricity consumption data for lighting and small power, accounting for variations of up to 17% in electricity consumption. Although these results provide an insight into the impact of occupant behaviour, it does not provide a usable methodology for modelling the impact of occupants on small power electricity consumption. Hence, a second study was conducted to investigate the relationship between users, computers and the overarching role of the organisation through detailed monitoring of 8 laptops and 5 desktop computers over a 2-month period. Results suggest that equipment specification can influence more than just power levels, influencing the time spent on different operating modes and the probability that the computer will be switched off at the end of the day. Users in the same job role using the same equipment were observed to have divergent energy consumption levels and usage profiles, suggesting that attitudes can have a greater impact on energy consumption than job requirements alone.

Objective 5: Development of predictive models of small power

Two models were developed to estimate energy consumption of small power equipment. The decision for developing two separate models arose from the contrasting requirements for academic rigour and usability. Model 1 is based entirely on the random sampling of detailed monitored data, and addresses the first requirement. However, it fails to provide a usable framework for designers due to the need for detailed data that is not generally available at the design stage. Model 2 relies on a bottom-up approach and is informed by key research findings, providing a tool that is of greater use to the sponsor company and the wider industry. Both models demonstrated a good correlation between metered data and prediction ranges for monthly energy consumption as well as power demand profiles. Whilst the model based on monitored data provides estimates with greater granularity, bottom-up predictions were also observed to be representative of metered data, also providing a more usable tool for designers.

5.2 CONTRIBUTION TO EXISTING THEORY AND PRACTICE

The findings from this research project provide three contributions to existing theory and practice. These fall under the following definitions of original contribution: 'bringing new evidence to bear on an old issue'; 'taking a particular technique and applying it to a new area'; 'being cross disciplinary and using different methodologies' and 'adding to knowledge in a way that hasn't been done before' (Phillips, 1993).

Contribution 1

The first contribution consists of new monitored data for energy consumption and power demand profiles of individual small power equipment in use in contemporary office buildings. Data regarding the mean power demand and daily profiles for 17 small power devices was published in the Building Services Engineering Research & Technology journal. The findings were used to assess the validity of existing UK benchmarks. A subsequent study included detailed power demand profiles for 13 computers at 1-minute intervals. These we used to assess the variability of usage patterns amongst different types of computers and users. Annual energy consumption of small power equipment and lighting was also published in the Applied Energy journal and highlight variations of up to 75% amongst 4 different tenants in a multi-tenanted office building. Further data presented at the CIBSE Technical Symposium demonstrate variations in small power consumption as high as 73% by tenants occupying the same building. A paper recently submitted to Energy and Buildings includes daily power demand profiles and monthly energy consumption data for two offices occupied by the same company.

Contribution 2

The second contribution consists of a cross-disciplinary investigation into the factors influencing small power demand and consumption in office buildings. A study based on the Theory of Planned Behaviour demonstrated a statistically significant correlation between perceived behavioural control and electricity use for lighting and small power, accounting for

17% of the variation in electricity use by different tenants. Findings were presented at the International Conference on Innovation in Architecture, Engineering and Construction. A subsequent monitoring study at the equipment level identified that a user's attitudes may have a greater impact on variations in energy consumption than their job requirements alone. A novel method for evaluating energy consumption of computers using 'window-plots' was also developed and implemented, illustrating the uncertainty in power demand and time spent on individual operational modes. Findings also suggest that desktop computers have a higher probability of being switched on during and outside working hours than laptop computers.

Contribution 3

The third contribution consists of two validated models for estimating power demand profiles and energy consumption of small power equipment in offices. The first model is based on random sampling of detailed monitored data. Outputs can be used to predict energy consumption, power demand profiles and resultant internal heat gains, contributing to better predictions of cooling demand. The second model takes a bottom-up approach, relying on a combination of benchmark data and user inputs to characterise small power demand and consumption. A comparison of strengths and limitations of both tools was carried out, highlighting that although the model based on monitored data provides a methodology that is less reliant on assumptions, it also requires extensive monitored data, much of which is not available at the design stage. Meanwhile, the bottom-up approach provides a more usable tool with wider applicability to industry. Outputs from both tools were verified through a blind validation exercise, demonstrating a good correlation between predictions and metered data.

5.3 IMPLICATIONS/IMPACT ON THE SPONSOR

As the construction industry is becoming more aware of the shortfalls in energy performance of buildings, designers are facing increased drivers to predict operational energy use, going beyond simplified compliance calculations. Insight into the factors that influence variations in small power energy consumption and power demands, coupled with a usable prediction model, will allow the sponsor company to address requests for predictions of operational performance. This is of particular importance when designing high efficiency/low carbon buildings, as small power is likely to become a greater proportion of energy use, whilst also affecting cooling demands. The modelling tool also facilitates the dialogue between designers and clients, enabling a clear visualisation of the impact of certain variables (such as the equipment specification and hours of operation) on the resultant energy consumption and power demand.

This research project has also led to the development and publication of CIBSE Technical Memorandum (TM) 54, which provides guidance to designers on how to estimate operational energy use at the design stage. This publication has several positive implications for the sponsor company, placing it at the forefront of this service offering whilst also increasing its visibility amongst the industry as a research-focused and forward thinking organisation.

5.4 IMPLICATIONS/IMPACT ON WIDER INDUSTRY

Published data regarding the in-use energy performance of small power equipment, alongside the factors that influence variation in energy consumption, can be used widely by the industry to account for small power consumption in a more representative manner when predicting operational energy use. This data could also be used to inform better systems design based on realistic internal gains. The publication of a journal article providing a critical review of existing benchmarks highlighted the need for up-to-date benchmarks and will hopefully encourage more frequent reviews of published data.

Improved predictions of operational energy use can also be of benefit in a number of service offerings such as energy performance contracting, whereby energy conservation measures are implemented without up-front capital costs to the end-users. In such initiatives, the cost of the measures are covered by future energy savings, requiring increasingly accurate models for predicting operational energy use. Similarly, contractual obligations for achieving a certain level of energy efficiency such as a target DEC rating would also benefit from improved operational energy use predictions based on better estimates of small power consumption.

It is envisioned that key findings from the research can also be used to encourage informed discussions between designers, clients and occupiers regarding the impact of small power equipment on operational energy use. These can be used to steer company policies towards energy conscious ICT procurement practices and/or behaviour change initiatives.

Research findings were disseminated broadly through industry-based conferences (such as the CIBSE Technical Symposia) and publications (such as the journal of Building Services Engineering Research & Technology and the CIBSE Journal). The researcher was also invited to present at prestigious events such as Ecobuild 2013 and seminars hosted by RIBA and CIBSE.

The development and publication of CIBSE TM54 is likely to have a significant impact on the wider industry as it sets a methodology for evaluating operational energy use at the design stage. This is likely to promote further understanding into shortcomings of current practices as well as more informed predictions of energy use.

5.5 RECOMMENDATIONS FOR INDUSTRY/FURTHER RESEARCH

It is imperative that benchmarks be updated on a regular basis to account for the fast-paced developments in computer technology. Further research into the energy consumption of state of the art equipment should be undertaken and published frequently. Recent adoption of ‘thin client’ technology in educational buildings is likely to expand to other building types, and data regarding their energy performance would be highly beneficial. Insight into the impact of adopting said methodology would be beneficial both from an energy consumption perspective and as a strategy to mitigate internal heat gains.

Further research into small power consumption aimed at updating benchmarks could take a simpler approach than the one undertaken as part of this research project, focusing solely on measurement of power demand at different operational modes (irrespective of user behaviour as the latter can be characterised through detailed through detailed usage profiles). Meanwhile, a thorough investigation into variability of diversity factors in office building would be of great benefit to the industry, allowing for more robust estimates to be made for a wide variety of office buildings.

There is scope to develop a ‘hybrid’ version of the two models presented in this thesis whereby detailed monitoring data is used to directly characterise the usage profiles of individual equipment in a bottom-up tool. This could be achieved by disaggregating the specific power demand values from the profiles, resulting in profiles that refer to operational modes instead. This would require extensive detailed monitoring of different users but less so of different machines, as mean values for each operational mode could be entered manually. A key barrier to this approach however, is that if a machine is being used to the limits of its capability, it is likely to operate in higher operational modes (as discussed in Section 4.5). As such, applying the same profile to a machine with different specification would not be representative of the likely usage patterns. Further monitoring data of catering equipment would also be beneficial to inform more representative usage profiles in the bottom-up tool.

There is also scope to further implement the occupant behaviour questionnaire developed as part of this research project (detailed in Section 4.4). The same questionnaire can be used to assess the impact of occupant behaviour on variations of lighting and small power consumption on a wider range of buildings (with appropriately sub-metered zones). Information regarding the development of the questionnaire (found in Appendix F) can also be used to develop bespoke surveys focused on different behavioural characteristics.

Further validation of both models as well as the TM54 methodology would be beneficial to assess their applicability to diverse building types and uses. CIBSE is encouraging their members test out the TM methodology and feedback their results to inform future updates to the guidance document. It is envisioned that future iterations of the TM would refer to the bottom-up tool developed in this research project, aiming to encourage users to assess small power consumption and loads in a thorough, yet straightforward manner.

5.6 LIMITATIONS OF THE RESEARCH

At the onset of this EngD, the research covered a very broad scope, aiming to address the discrepancies between predicted and in-use energy performance of buildings as a whole. This resulted in a significant proportion of the research time being spent on the decision of an appropriate direction to pursue allowing for a smaller and more tangible scope to be covered. A clearer and more defined scope at the onset could have resulted in a greater volume of practical research being undertaken.

The research project was heavily reliant on monitoring data resulting in numerous barriers. The first one was gaining access and permission to buildings in which to undertake a monitoring study. Although the sponsor company's involvement in building design should support these efforts, clients were generally very protective about building performance data, often declining access to their buildings for post occupancy monitoring studies. The second biggest barrier was obtaining sub-metering data for small power consumption as is this end-use was often included in the same sub-meter as lighting. This resulted in extensive efforts to monitor individual sub-circuits through the use of portable energy profilers, also presenting a further barrier as clients and facilities managers were often reluctant to grant access to distribution boards.

Obtaining access to small power monitoring data at the equipment-level also presented numerous challenges, going beyond issues pertaining to the accessibility to buildings and tenant zones. Limited availability of monitoring equipment (i.e. ploggs) coupled by their short communication range to data logging computers limited the number of equipment that could be monitored simultaneously. In addition, only a small number of different computer models were procured by the company investigated in the research project, also limiting the possible scope of the monitored sample. These factors resulted in a small sample size, which was investigated however, in a multi-disciplinary and thorough manner. Findings, although based on a small sample of computers, reflect real operation and usage patterns, providing insightful information on the complex factors influencing the energy consumption of computers. Results are not exhaustive and will not cover every possible user-computer combination, yet they can be used to inform better estimates of small power consumption by highlighting the underlying complexities between occupant behavior and small power energy consumption.

Despite these limitations, this research project has successfully achieved its overarching aim by providing a better understanding of the factors that generate variability in small power consumption in commercial buildings, demonstrating how these can be accounted for in representative, building specific estimates of operational energy use. Five specific objectives were fulfilled, generating key outcomes that contributed to the achievement of the thesis' aim. The research has culminated in two models for estimating energy consumption of small power equipment addressing both the academic and industrial requirements. Both models are also capable of estimating power demand profiles of small power equipment, allowing for better estimates of internal heat gains to be generated. Furthermore, the research has supported the development of a guidance document on how to evaluate operational energy performance of non-domestic buildings at the design stage. Cumulatively, the outcomes of this project have great scope to improve current practices for predictions of energy consumption in buildings.

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APPENDIX A ANALYSIS OF ELECTRICITY CONSUMPTION FOR LIGHTING AND SMALL POWER IN OFFICE BUILDINGS (PAPER 1)

Full Reference

Menezes, A., Cripps, A., Bouchlaghem, D. and Buswell, R., 2011. *Analysis of Electricity Consumption for Lighting and Small Power in Office Buildings*. CIBSE Technical Symposium, DeMontfort University, Leicester UK, 6th - 7th September.

Abstract

There is significant evidence to suggest that buildings do not perform as well as expected, and this is commonly referred to as the 'performance gap'. Energy compliance calculations for Building Regulations in England and Wales do not include sources of energy consumption in buildings such as small power, catering, external lighting and vertical transportation (i.e. lifts and escalators). These so called 'unregulated' loads are therefore rarely included in building energy models, and the lack of feedback regarding the in-use performance of buildings makes it harder for designers to quantify their impact on the overall energy consumption of a building. Aiming to address these issues, this paper provides an analysis of monitored electricity consumption in two multi-tenanted office buildings, with one tenant in common in both buildings.

This paper focuses on tenant electricity consumption, including lighting and small power. Detailed analysis of the monitored data demonstrates significant variation between the electricity consumption of different tenants occupying the same building whilst performing similar activities. Elements such as lighting controls, hours of occupancy and management decisions are observed to have a significant impact on such variations. Further analysis of half-hourly energy consumption data is also provided, in addition to a detailed breakdown of small power energy consumption due to individual office equipment.

Future work will build on this study and aim to develop evidence based benchmarks for energy consumption in office buildings. It will include a 'tailoring' component allowing the benchmarks to be adjusted according to profiles of occupancy and management behaviour, as well as workstation density and the specification of energy consuming equipment. It is expected that such benchmarks will inform designers about the impact of each of these parameters on the measured energy consumption of buildings.

Keywords – Performance gap, energy performance, offices, lighting, small power

Paper type – Conference Paper

1 INTRODUCTION

With the increasing demand for more energy efficient buildings, the construction industry is faced with the challenge to ensure that energy efficiency is implemented beyond design predictions. However, there is extensive evidence to suggest that buildings are not performing as well as predicted. The PROBE studies (Post-occupancy Review of Buildings and their Engineering) investigated the performance of 23 non-domestic buildings previously featured as 'exemplar designs' in the Building Services Journal (Bordass et al., 2001). The research project ran from 1995 to 2002, highlighting the lack of feedback regarding the actual performance of buildings. It also brought to light the so called 'performance gap', suggesting that the actual energy consumption in buildings will usually be twice as much as predicted .

More recently, in 2008, the Royal Institute of British Architects (RIBA) and the Chartered Institution of Building Services Engineers (CIBSE) launched CarbonBuzz, a free online platform allowing practices to share and publish building energy consumption data anonymously (CarbonBuzz, 2011). It enables designers to compare predicted and actual energy use for their projects, whilst also allowing for comparison against benchmarks and data supplied by other participating practices. Figure 1 illustrates the gap between predicted and actual electricity consumption in three building types: general offices, schools and university campus. The graph depicts the median predicted and median actual electricity consumption for the buildings within the database, which are assumed to be broadly representative of each sector. As shown, the measured electricity demands are approximately 60% to 70% higher than predicted in both the schools and general offices, and over 85% higher than predicted in university campuses.

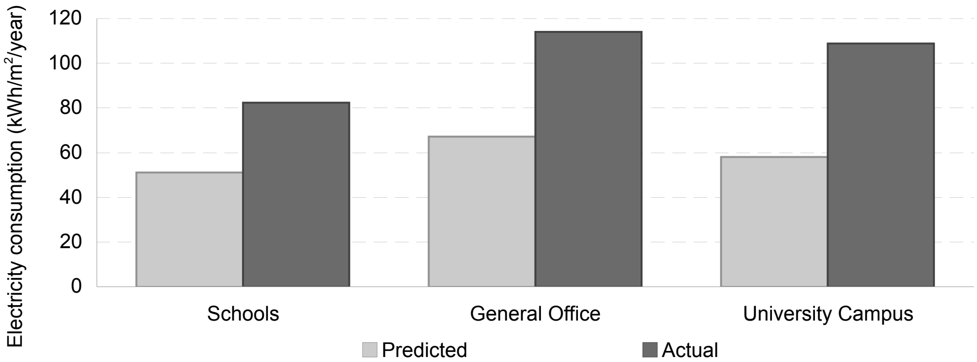

Figure 1: CarbonBuzz median energy use per sector - Predicted vs. Actual

Previous work by the authors has highlighted that the causal factors for such discrepancies relate to both predictive and in-use performance, implying that current predictions tend to be unrealistically low, whilst actual energy performance is usually unnecessarily high (Menezes et al., 2011). However, the overall problem could be interpreted as an inability of both current modelling techniques and modellers to represent realistic operation of buildings through the use of inputs and parameters that are representative of occupied buildings in-use. This in turn can be associated with the lack of feedback regarding the use and operation of buildings as well as the resulting energy consumption. Currently, there is a significant lack of information concerning the energy performance of our existing building stock (Lowe and Oreszczyn, 2008). A continued absence of such data is likely to lead to a progressive widening of the gap between theory and practice and a failure to achieve strategic goals (Oreszczyn and Lowe, 2010).

In order to bridge this 'Performance Gap', further understanding on the impact of small power and other unregulated energy loads is crucial. Emphasis on these end-uses allows for investigation of the impact of occupants and management behaviour and the resulting impact on the electricity consumption of different tenants. Variation in small power consumption is of particular interest to this study as small power is not currently included in the Building Regulations for England and Wales, and as such is not within the compliance modelling calculations. Aiming to address this issue, this paper provides an analysis of monitored data for electricity consumption due to lighting and small power in two office buildings in England.

2 METHODOLOGY

Taking a case study approach, this paper focuses on the energy performance of two multi-tenanted office buildings located in London and Bristol. The assessment concentrates on electricity consumption due to lighting, small power equipment and catering equipment, in line with the Energy Assessment and Reporting Methodology (EARM). This widely recognised methodology was originally developed for the PROBE studies and was later published by CIBSE as a technical memorandum (CIBSE TM22). This document describes a method for assessing the energy performance of an occupied building based on metered energy use, and includes a software implementation of the method. It can be used to identify underperforming buildings and systems, indicating the causes of poor performance and benchmarking procedures (CIBSE, 2006). Figure 2 illustrates the underlying structure of the TM22 methodology, depicting the breakdown of energy consumption by end-uses (such as lighting, small power and ventilation) whilst highlighting the impact of low-level factors such as hours of use and equipment efficiency.

Considering the focus of the study was on lighting and small power, it was not necessary to undertake a full TM22 assessment of each building. However, in order to set the context for further in depth investigations, one of the buildings was assessed in full, highlighting the impact of lighting and small power on the overall electricity consumption of the building. Considering the building contains 32 zones occupied by 4 different tenants, assumptions were made with regards to the installed equipment and lighting in the tenant areas in order to facilitate this initial TM22 assessment. This was deemed appropriate as the purpose of this initial assessment was to provide context with regards to the energy use breakdown of different end-uses. In the second building, electricity consumption due to building services was not considered and the assessment considered only the tenant electricity consumption (including lighting and small power due to office and catering equipment). In both buildings, the detailed TM22 assessment of lighting and small power in the tenant zones relied on studies of 'sample' zones occupied by different tenants.

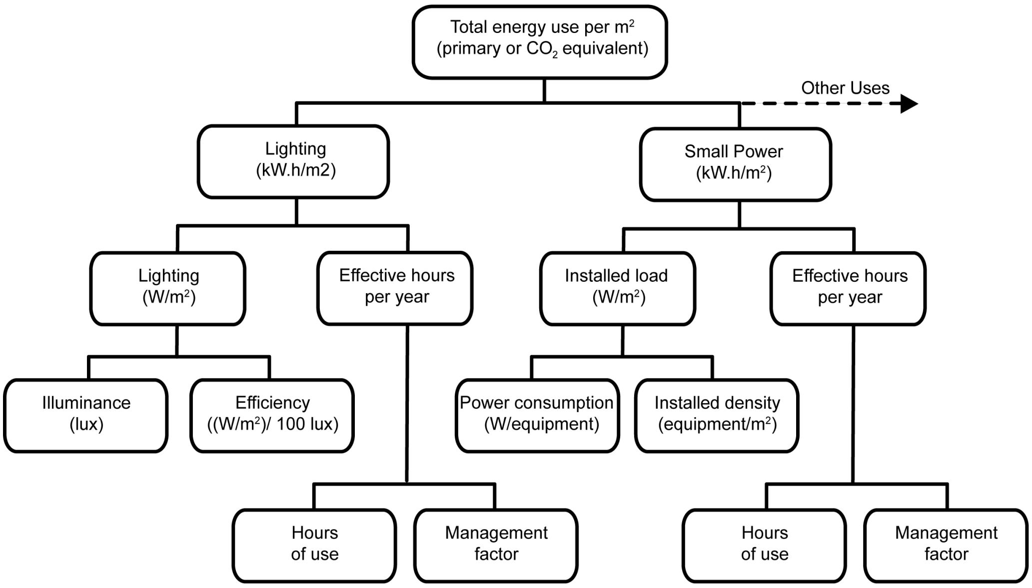

Figure 2: TM22 'Tree Diagram' illustrating the breakdown of energy use

2.1 Building Description

Building 1 is located in central London and accommodates the offices of four different companies throughout its seven floors and basement. It includes an atrium that reaches all floors (except the basement). Each floor comprises mainly of open-plan office spaces with a treated floor area of approximately 2,000m^2. The ground floor houses a large reception and the basement houses meeting rooms and cellular offices. The building is fully air-conditioned, three rooftop air-handling units (AHUs) provide heating/cooling as well as fresh air to all floors and the atrium. A separate system provides heating for the basement, whilst fan coil units (FCUs) provide cooling to the meeting rooms and small individual offices

Figure 3 illustrates the metering strategy for the supply of electricity to Building 1. As shown, the landlord is responsible for the electricity consumed by all air conditioning equipment including the AHUs, FCUs, chillers, pumps and fans as well as the BMS and other control equipment. The lighting throughout the common areas of the building as well as the toilets is also supplied and maintained by the landlord. As such, the energy supplied for the landlord services is metered together, with no sub-metering for individual end-uses. Meanwhile, the electricity supplied to the tenants for lighting, small power equipment and catering in each of the floors is metered separately. A total of 32 sub-meters provide a further breakdown for each of the 4 zones in each floor: North-East (NE), Northwest (NW), Southeast (SE) and Southwest (SW).

Building 2 is located in Bristol city centre and accommodates offices of four different tenants over four floors. Each floor comprises mainly of open-plan office spaces with a treated floor area of approximately 3,500m^2. The ground floor houses a large reception and a cafe (for which the electricity and gas usage is metered separately from the rest of the building). The building is fully air-conditioned via FCUs, and has two atria with full height glazing providing natural lighting throughout the building.

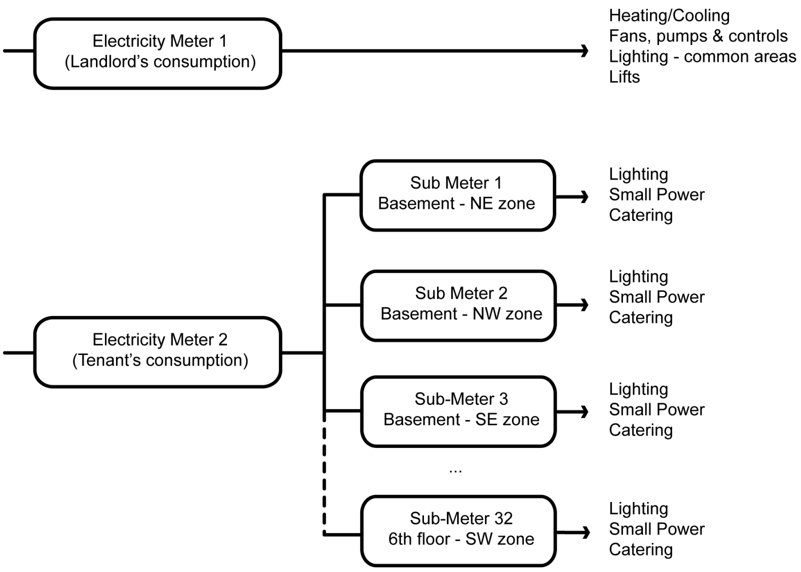

Figure 3: Metering strategy for the supply of electricity to Building 1

Figure 4 illustrates the metering strategy for the supply of electricity to Building 2. Similarly to Building 1, the landlord is responsible for the electricity consumed by all air conditioning equipment as well as the BMS and lighting throughout the common areas of the building. Once again, the electricity supplied for the landlord services is metered together, with no sub-metering for individual end-uses. Meanwhile, the electricity supplied to the tenants is not only sub-metered by zone, but also by end-use, with lighting and small power having separate sub-meters in each individual zone. As such a total of 32 sub-meters provide a breakdown for lighting and small power in each of the 4 zones in each floor: Core 2.1, Core 2.2, Core 3 and Core 5.

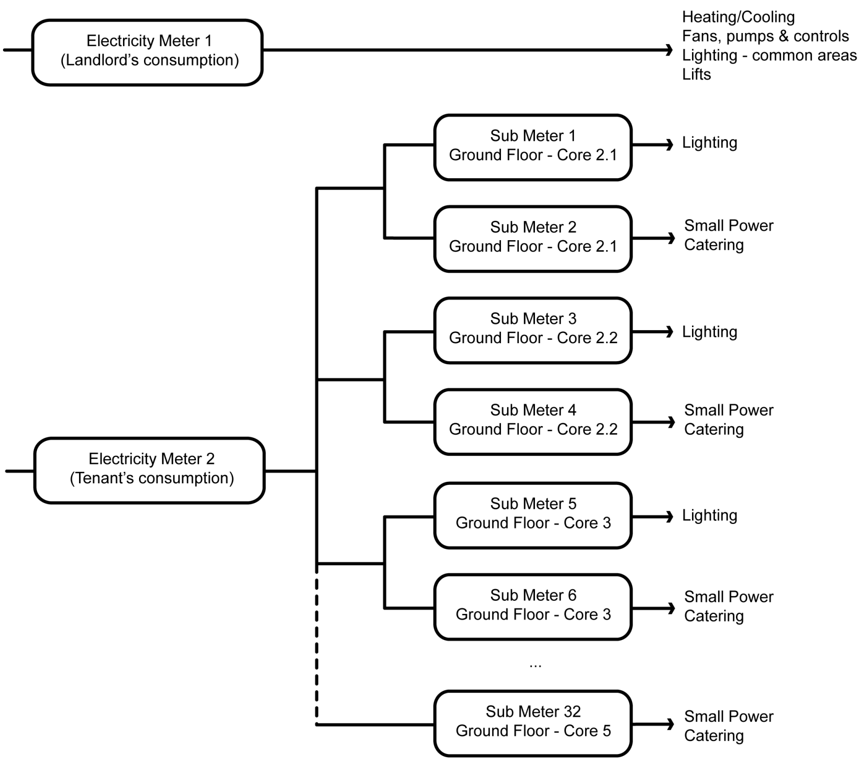

Figure 4: Metering strategy for the supply of electricity to Building 2

2.2 Monitoring Process

Monthly meter readings were taken and recorded over a one-year period for each of the electricity sub-meters in both buildings. In Building 1 this consisted of a single reading per zone (including lighting and small power) whereas in Building 2, two readings per zone were acquired due to the separate sub-metering for lighting and small power. Monthly and annual consumption data was then compiled for each of the tenants and normalised by floor area occupied.

Portable 3-phase energy profilers (SP Max, 2011) were connected to the electricity supply in individual tenant zones in each of the buildings in order to monitor half hourly consumption. Focus was given to areas occupied by the same tenant in both buildings to establish any variation in the electricity demand profile in different offices. In Building 2, interval data for lighting and small power were obtained simultaneously for fair comparison. Monitoring of sub-metered electricity was undertaken for approximately 1 month in each of the zones, and results were cross-checked against meter readings for verification.

Combined plug monitor / loggers (ZigBee Plogg, 2011) were connected to individual small power office equipment such as laptops, computer screens and docking stations. These were also used to monitor the electricity consumption of catering equipment such as fridges, microwave ovens and coffee machines, and logged 5-minute interval electricity consumption data over a 1 week period. Averages during ‘in-use’, ‘stand-by’ and ‘off’ modes were calculated using the monitored data for each of the equipment. These values were then used to replace typical nameplate-rating inputs necessary for the successful completion of the TM22 assessment.

3 RESULTS AND DISCUSSION

Figure 5 illustrates the electricity consumption breakdown by end-use for Building 1, providing context for further analysis of lighting and small power. It also illustrates the split between landlord and tenant consumption, demonstrating that the landlord is only responsible for 30% of the electricity used in the building, with the tenants being responsible for the remaining 70%. As seen, lighting accounts for 24% of the annual electricity consumption, followed closely by small power, which accounts for 18% of the total. Server rooms are the single largest consumers of electricity in the building, almost equating to the combined consumption by fixed building services (i.e. chillers plus fans, pumps and controls). Note that the sub-metering of the server rooms in Building 1 include the electricity demand for running the servers themselves as well as the local cooling demands (usually met by split-system air conditioning units).

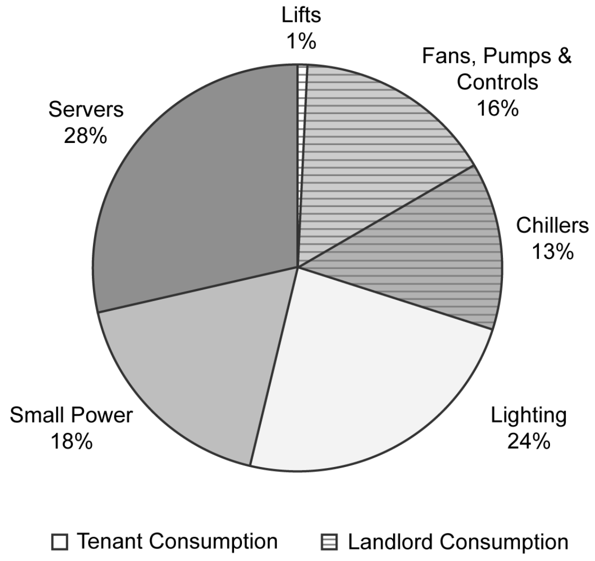

Figure 5: Electricity consumption breakdown by end-use in Building 1

3.1 Annual Electricity Consumption per Tenant

Figure 6 illustrates the annual electricity consumption by each of the tenants in Building 1 (normalised by the floor area they occupy). This includes lighting and small power but excludes server rooms. It is worth noting that the lighting specification and controls are consistent throughout the entire building. This consists of a 'DALI' (Digital Addressable Lighting Interface) system whereby the installed fixtures have the capability of being controlled by a variety of factors such as daylight and/or motion sensors, to suit the need of the specific tenants. However, it is up to the individual tenants to adopt such control strategies by installing and commissioning the necessary sensors, otherwise the lighting strategy is limited to manual controls of the individual zones in the building. To date no tenants have taken advantage of the DALI system and thus they rely on manual switches to control their lighting levels.

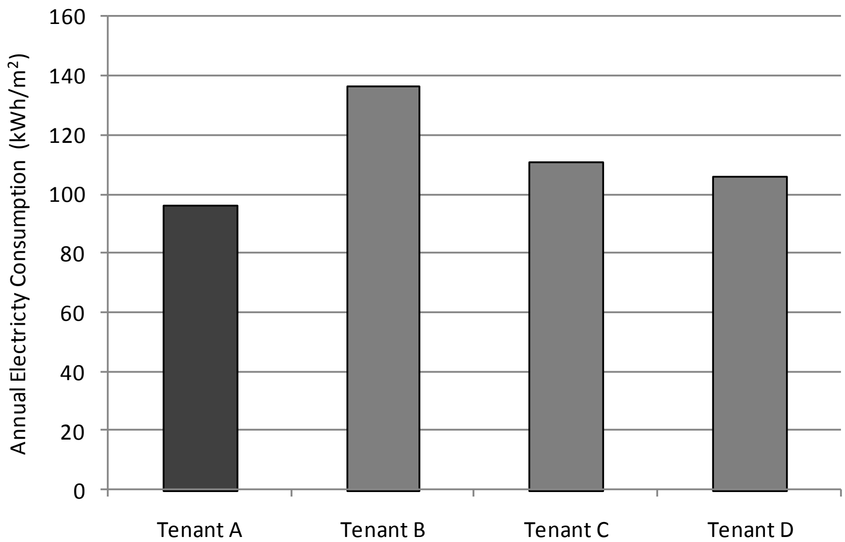

Figure 6: Annual electricity consumption per tenant in Building 1

With regards to catering facilities, all floors have provisions of similar size and nature (consisting mainly of an instant hot water heater, a microwave, a dishwasher and a full size fridge). Some floors have additional coffee machines and/or vending machines, and tenant C has a large bar with multiple fridges on the ground floor. It is worth noting however, that variations in catering energy consumption can be largely due to hours of usage rather than intensity of installed equipment. Tenant A for example have 2 microwave ovens in a single kitchen yet monitored data has revealed that one of them is rarely used, hence having a second microwave oven has virtually no impact on their catering energy consumption.

In regards to small power, a fairly consistent volume of office equipment is present throughout the building. Despite their different nature of work, all 4 tenant companies have similar occupation densities and office equipment specifications. Most workstations consist of a computer screen, laptop and docking station as well as phone. Some workstations have individual desk lamps, personal fans and/or desktop printers. In addition, all floors have large printer/copiers (typically 6-8 per floor) as well as projectors and/or flat screen displays in meeting rooms.

As seen, the highest consumer (Tenant B) uses approximately 40% more electricity per year than the lowest consumer (Tenant A). Informal interviews with the building occupants uncovered a number of behavioural elements that could contribute to this significant variation. For example, employees of Tenant B are instructed to leave their computers on overnight for IT upgrades. As such, a large quantity of electricity is used outside the normal operating hours of the building, accounting for a significant portion of their overall consumption. Similarly, some employees of Tenant C often leave their computers on at the end of the day so that time-consuming tasks, such as high quality rendering, can be performed overnight. On the other hand, employees of Tenants A and D are encouraged to save energy by turning off their computers and screens at the end of the day. Tenant A has also trained their facilities co-ordinators to switch off printer/copiers and non-essential catering equipment such as coffee machines at the end of each day.

Figure 7 illustrates the electricity consumption in each of the sub-metered zones within Building 1 (normalised by floor area). The dark grey bars represent the zones occupied by Tenant A. Here, the highest consuming zones (3-03 and 4-03) are occupied in a very similar manner, both being located on the South-East corner of the building, containing high density of workstations as well as substantial printing facilities. Meanwhile, some of Tenant A's least consuming zones (3-01 and 4-01) are also very similar in layout, this time with lower workstation density due to the existence of a catering kitchen and small reception area on each of the floors. Despite the fact that both catering kitchens contain equipment with high power demand (such as dishwashers, instant water heaters and microwave ovens) these are only used sparingly. In addition, the seating areas in the catering kitchens occupy a significant proportion of the floor area in each of the zones and virtually no small power electricity in consumed in those areas. Zone 3-02 has surprisingly low electricity consumption considering it has no large areas of seating such as in zones 3-01 and 4-01. However, the zone has no printing facilities and it also contains a small meeting room, which reduces the overall workstation density of the zone. Meanwhile, zone LG-02 consists mainly of meeting rooms, most of which are heavily equipped with multimedia equipment for presentations and conference calls. These meeting rooms are usually fully booked and fairly high electricity consumption would suggest that the use of small power is fairly high in this zone (which might otherwise be expected to be a low consuming zone).

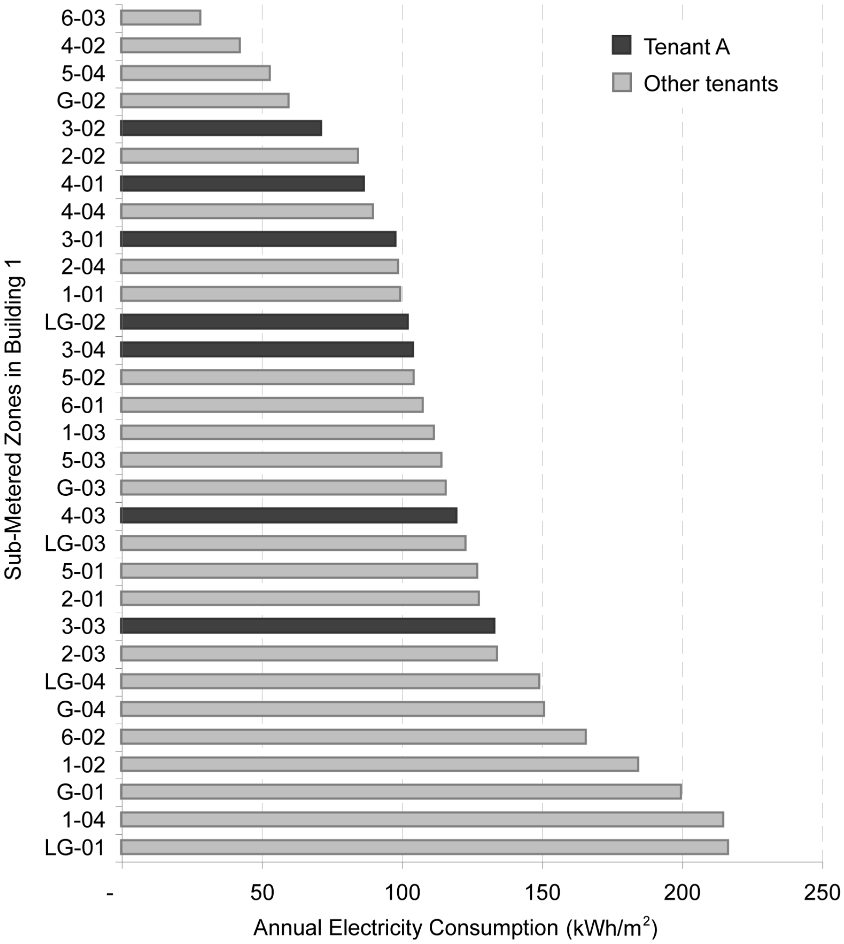

Figure 7: Electricity consumption in individual zones of Building 1

Figure 8 illustrates the annual electricity consumption by each of the tenants in Building 2 (normalised by the floor area they occupy). Once again it includes lighting and small power but excludes server rooms. Similarly to Building 1, the lighting specification and controls are consistent throughout the entire building and installed equipment is of a similar nature and quantity. It is worth mentioning however, that the lighting controls for Building 2 are of higher specification than in Building 1, relying both on daylight and occupancy sensors to switch lights on and off in different zones. This allows for the lighting fixtures in the perimeter of the building to be dimmed down when daylighting levels are sufficient to provide adequate lighting to the working areas near windows. In addition, the passive infra-red (PIR) sensors prevent lights from staying on when the zone is unoccupied. This might be one of the main contributors to the fact that tenant electricity consumption in Building 2 is generally lower than in Building 1. With regards to catering facilities, each floor has a kitchen of a similar size and nature (consisting mainly of an instant hot water heater, a microwave, a dishwasher and a large fridge).

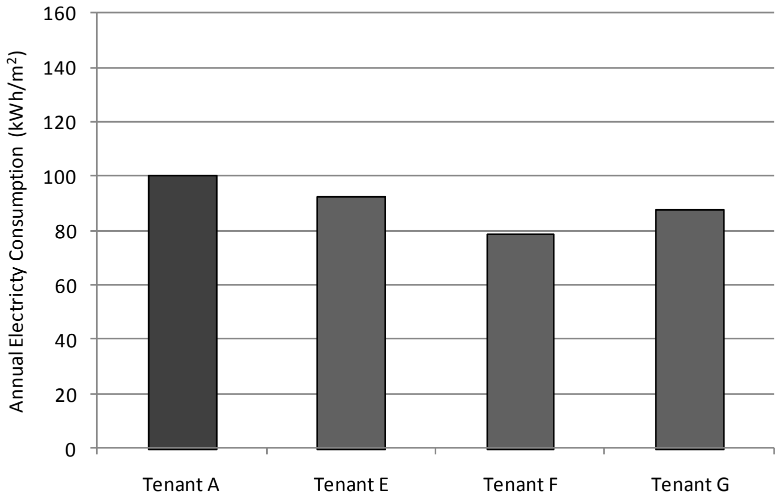

Figure 8: Annual electricity consumption per tenant in Building 2

As seen, the highest consumer (Tenant A) consumes approximately 30% more electricity than the lowest consumer (Tenant F). Further investigation into the causes of such variation revealed that the zone occupied by Tenant F houses a call centre that operates only during fixed hours. This means that that unlike most of the other tenants, employees of Tenant F do not generally work beyond regular working hours, resulting in lower electricity consumption both due to lighting and small power. It is also worth noting that Tenant F occupies a single zone that is mostly located in the perimeter of the building which is likely to result in lower lighting energy use. Meanwhile, Tenants E and G undertake similar tasks, having similar equipment specification and office space layout. Together they occupy approximately 75% of the building's floor area and their numerous zones vary from open plan office spaces, to meeting rooms and seating areas.

Figure 9 illustrates the electricity consumption in each of the sub-metered zones within Building 2 (normalised by floor area). Once again the dark grey bars represent the zones occupied by Tenant A. Differently to Building 1, Tenant A's zones in Building 2 seem to consume almost exactly the same amount of electricity with virtually no variation between them. This is somewhat surprising considering that both zones are occupied and used in fairly different ways. Zone 3-5 houses a small kitchen, meeting rooms and a seating area, as well as open plan office spaces, whereas zone 3-2.2 is fully occupied by open plan office spaces. Considering the virtually identical electricity consumption in both zones, it is possible to assume that the increased use of electricity due to catering equipment is somewhat cancelled out by the additional seating area and the meeting rooms, where less electricity consumption is usually observed when compared to open plan office spaces. Another surprising observation from Figure 9 is that Tenant A's zones are not within the worst consuming zones, which might have been expected considering they were the highest consumers according to Figure 8. This would suggest that there is significant variation in electricity consumption on the zones occupied by the other tenants. It is worth mentioning that zone 3-2.1 is omitted from Figure 9 as it has been unoccupied for several months, and would not provide a fair comparison against the other zones.

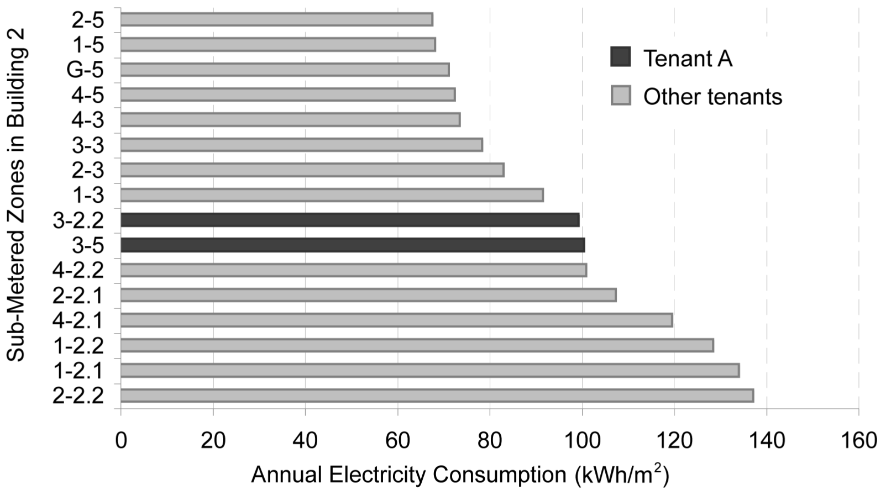

Figure 9: Electricity consumption in individual zones of Building 2

Figure 10 illustrates the electricity consumption by all tenants in Building 1 and Building 2. It also displays typical (TYP) and best-practice (BP) benchmarks for both lighting and small power in UK office buildings according to the Energy Consumption Guide 19. Note that in Building 1 the lighting and small power are metered separately, but this is not the case in Building 2, which explains the different breakdown of information provided in the figure. As seen, Tenant A is the highest consumer in Building 2 and the lowest consumer in Building 1, but their electricity consumption is also fairly consistent in both buildings. With the exception of Tenant A, all Building 2 tenants are in the lower consuming half of the graph and similarly all Building 1 tenants are in the higher consuming half of the graph. This could be related to the fact that Building 2 has better lighting controls than Building 1, as previously discussed, which is further substantiated by the fact that all Building 2 tenants have lighting consumption levels below the typical benchmark.

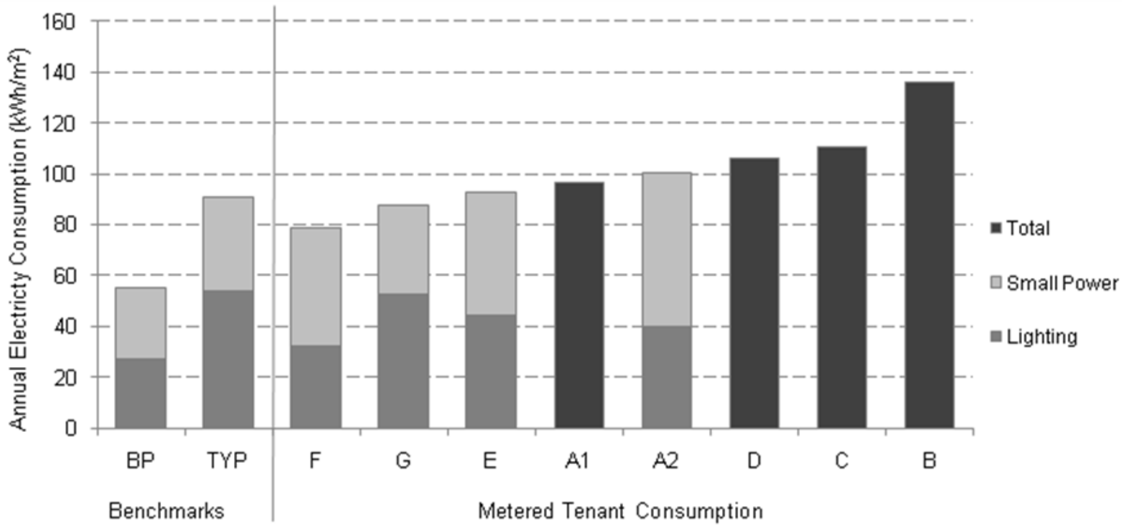

Figure 10: Annual electricity consumption by all tenants in both buildings

Looking further into the consumption for Building 2 tenants, it is possible to see that there is significant variation in lighting consumption amongst the different tenants. Considering that the lighting specifications and controls are consistent throughout the entire building, this variation could be attributed to two elements: 1) hours of occupancy and 2) location of the zones (which determines the amount of daylighting available). Tenant F, the lowest consuming tenant with regards to lighting, has a combination of both well day lit zones and low hours of occupancy. They occupy a single zone in the building that is mostly located on the perimeter, and as previously discussed, Tenant F employees work for a smaller number of hours when compared to other tenants. They do however consume a significant amount of electricity for small power, comparable to that of the highest consumer in Building 2 (Tenant A). Meanwhile, the tenant with highest lighting consumption (Tenant G) also has the lowest small power consumption, suggesting that many of their zones are indeed occupied by meeting rooms and seating areas with low installed equipment densities.

3.2 Half Hourly Electricity Consumption

Figure 11 illustrates the half hourly electricity consumption in one of zones occupied by Tenant A in Building 1. The electricity consumption data is normalised by the floor area covered by the sub-meter being monitored and represents the instantaneous electricity demand in Watts per m^2.

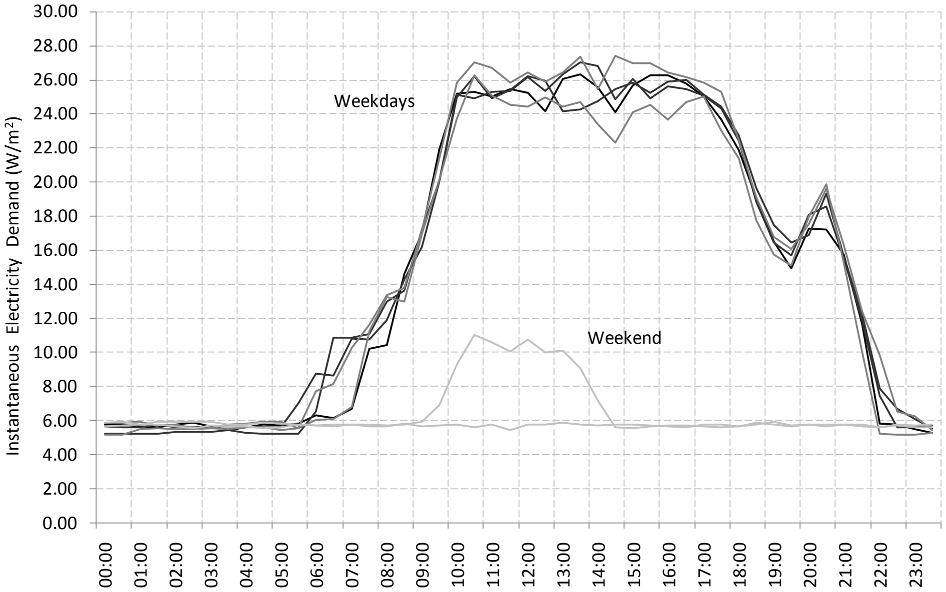

Figure 11: Half hourly electricity use by Tenant A in Building 1

As seen the base load is approximately 6 W/m^2 outside working hours. The electricity demand starts to escalate around 06:00 peaking at approximately 26 W/m^2 by 10:00. This can be associated with the arrival of employees, turning on the lights. This will usually be followed by office/catering equipment being used. From 10:00 to 17:00 the demand remains fairly high, varying between 22-28 W/m^2, eventually decreasing to approximately 16 W/m^2 by 19:30. This can be associated with equipment being turned off as employees leave the office. A steep rise in the demand is then observed at approximately 20:30, followed by a fairly quick decrease, bringing the demand down to the base load at around 22:00. This late peak can be associated with the cleaning schedule of the building. It is assumed that the rise in demand is due to the use of vacuum cleaners as well as the dishwasher being turned on. The electricity demand during the weekend is fairly constant at a similar base load to the evenings. The only deviation occurs on Saturday between 9:00 and 15:00 when the electricity demand rises to approximately 10 W/m^2. This can be associated to a small number of employees going into the office to work.

For comparison, Figure 12 illustrates the half hourly electricity consumption profile for a zone occupied by Tenant A in Building 2. Similarly to Building 1, the electricity demand starts to escalate around 06:00, but it peaks slightly earlier, by 09:00. The peak demand is very similar to Building 1 at approximately 26 W/m^2, and variations throughout the day are of very similar nature and size. A steep decrease in demand is observed around 19:00 and unlike Building 1 there is no cleaning peak following the departure of the employees. This is due to earlier cleaning schedule in building 2 in combination with employees leaving between 17:30 and 19:30. This results in a fairly smooth decrease in demand at the end of each working day. Similarly to Building 1, there is also a small peak in demand on Saturday due to some employees coming into the office.

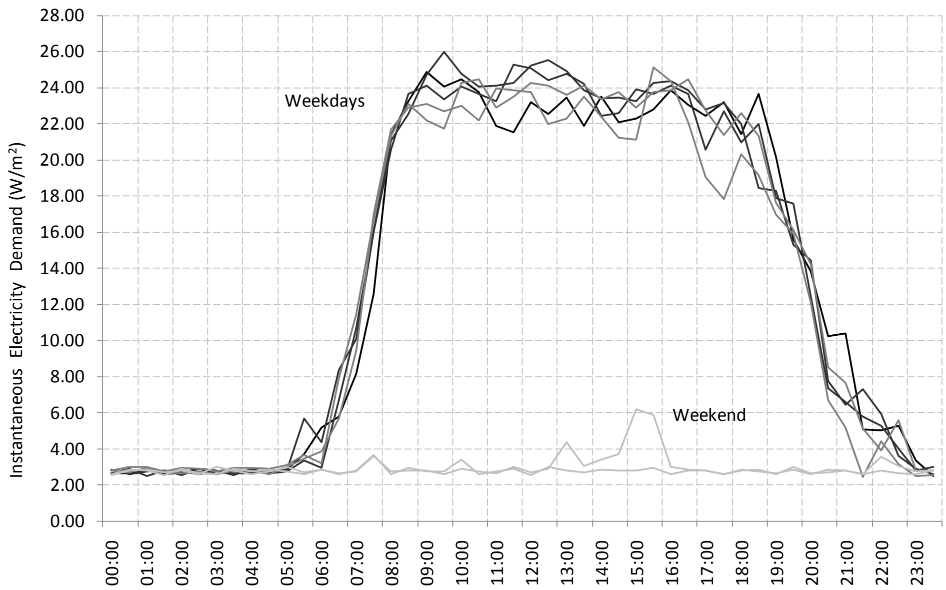

Figure 12: Combined half hourly electricity use by Tenant A in Building 2

3.3 Electricity Consumption by Different Equipment

The TM22 assessment carried out in Building 1 allowed for a detailed analysis of the electricity consumption by different small power equipment used throughout the building. This was further enhanced by the use of plug monitors connected to individual piece of equipment, monitoring their instantaneous electricity demand, allowing for assumptions on nameplate-ratings to be eliminated from the TM22 methodology. Figure 13 illustrates the annual electricity consumption by each of the small power equipment monitored as part of the study. It covers the installed equipment in the zones occupied by Tenant A in Building 1, and is normalised by floor area. As seen, desktops and laptops are responsible for the largest share of the electricity consumption at 17.5 kWh/m^2/year, followed closely by computer screens at 14.6 kWh/m^2/year. Photocopiers are also responsible for a significant portion of the electricity consumption, at 6.2 kWh/m^2/year, but their impact is only about 30% of that of computers. Coffee machines and fridges consume a similar amount at approximately 2 kWh/m^2/year. Desk lamps, microwave ovens and dishwashers all consume less than 1 kWh/m^2/year. These results demonstrates that power management functions for computers and screens, as well as behaviour change campaigns aimed at getting employees to switch off their computers at the end of the day could have a significant impact on electricity consumption.

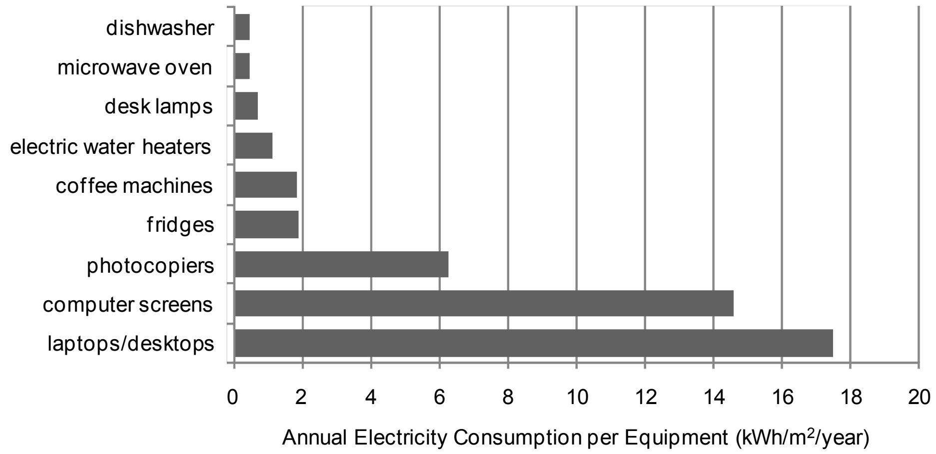

Figure 13: Annual electricity use per equipment by Tenant A in Building 1

4 CONCLUSION

This paper has discussed the existence of a gap between predicted and measured energy consumption in non-domestic buildings. It highlighted that a significant lack of information regarding actual energy consumption in buildings might be a leading cause in this performance gap. Aiming to address this issue, two case studies were presented whereby electricity consumption data for lighting and small power in office buildings were analysed and compared.

Key findings from the study highlighted a significant variation in electricity consumption by different tenants in both buildings. Tenants in Building 2 generally consumed less electricity than those occupying Building 1 and that can be partially attributed to better lighting controls in the former. In addition, variations in workstation density and office space layout were also seen to contribute to the variations in electricity consumption. Management decisions, such as the running of IT updates outside of occupancy hours, were seen to have a significant impact on electricity use, having been observed in the highest consuming tenant. Meanwhile, tenants with fixed working hours were seen to have significantly lower consumption of electricity due to lighting. The analysis of data for Tenant A, which occupied zones in both buildings, demonstrated that the attitudes and behaviour of a company might transcend the immediate surroundings of the building being occupied. Similar electricity consumption profiles suggest that management protocols and behaviours might have more impact on energy consumption than previously anticipated.

Overall the study has highlighted the need for better understanding of occupancy patterns and behaviour in office buildings. Variations in the electricity consumption of different tenants occupying the same building have demonstrated that modelling software would need to account for different occupancy patterns and behaviours if realistic predictions are to be achieved.

5 FUTURE WORK

This paper has identified a need for further understanding of the impact of occupant and management behaviour on electricity consumption in buildings. As such, future work will include further monitoring of different office buildings occupied by diverse types of tenants. It is envisaged that a survey will be developed for both occupants and facilities managers to be distributed in buildings being monitored as part of this research. These will be aimed at understanding the impact of varying attitudes and behaviours regarding energy use in buildings, with the ultimate aim of determining the impact of these behaviours on the overall energy consumption of buildings. Information gathered from the surveys will be used to develop evidence based benchmarks for energy consumption in office buildings. These will include a 'tailoring' component allowing the benchmarks to be adjusted according to profiles of occupancy and management behaviour, as well as workstation density and the specification of energy consuming equipment. It is expected that these benchmarks will inform designers about the impact of each of these parameters on the measured energy consumption of buildings, and support efforts to reduce energy use.

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APPENDIX B PREDICTED VS. ACTUAL ENERGY PERFORMANCE OF NON-DOMESTIC BUILDINGS: USING POST-OCCUPANCY EVALUATION DATA TO REDUCE THE PERFORMANCE GAP (PAPER 2)

Full Reference

Menezes, A., Cripps, A., Bouchlaghem, D., Buswell, R., 2012. Predicted vs. actual energy performance of non-domestic buildings: Using post-occupancy evaluation data to reduce the performance gap. *Applied Energy*, Vol. 97, pp. 355–364.

Abstract

With the increasing demand for more energy efficient buildings, the construction industry is faced with the challenge to ensure that the energy performance predicted at the design stage is achieved once a building is in use. There is, however, significant evidence to suggest that buildings are not performing as well as expected and initiatives such as PROBE and CarbonBuzz aim to illustrate the extent of this so called ‘performance gap’. This paper discusses the underlying causes of discrepancies between energy modelling predictions and in-use performance of occupied buildings (after the twelve month liability period). Many of the causal factors relate to the use of unrealistic input parameters regarding occupancy behaviour and facilities management in building energy models. In turn, this is associated with the lack of feedback to designers once a building has been constructed and occupied.

The paper aims to demonstrate how knowledge acquired from Post-Occupancy Evaluation (POE) can be used to produce more accurate energy performance models. A case study focused specifically on lighting, small power and catering equipment in a high density office building is analysed and presented. Results show that by combining monitoring data with predictive energy modelling, it was possible to increase the accuracy of the estimate to within 3% of actual electricity consumption values. Future work will seek to use detailed POE data to develop a set of evidence based benchmarks for energy consumption in office buildings. It is envisioned that these benchmarks will inform designers on the impact of occupancy and management on the actual energy consumption of buildings. Moreover, it should enable the use of more realistic input parameters in energy models, bringing the predicted figures closer to reality.

Key words - Building energy modelling, energy benchmarks, energy performance, performance gap, post-occupancy evaluation

Paper type – Journal Paper

1 INTRODUCTION

There is extensive evidence to suggest that buildings usually do not perform as well as predicted (Bordass et al., 2001; Bordass et al., 2004; Demanuele, 2010; PROBE, 2011). This is often attributed to the lack of feedback to designers after handover, inhibiting improvements both to existing buildings and future designs. The practice of Post-Occupancy Evaluation (POE) aims to address this issue by evaluating the performance of a building after it has been built and occupied to provide designers with valuable feedback on its actual performance in-use. This paper aims to demonstrate how knowledge acquired from POE can be used to produce more accurate energy performance models. The study focuses on electricity consumption due to lighting, small power and catering equipment, rather than thermal loads.

In recent years, Building Regulations in England and Wales have become increasingly stringent, demanding higher standards of energy performance. This can be linked to the implementation of the European Energy Performance of Buildings Directive (EBPD) as well as the Government's legally binding commitment to reduce UK carbon dioxide emissions by 80% by 2050 in relation to the 1990 baseline (Climate Change Act, 2008). As a result, all new buildings must achieve a Building Energy Rating (BER) lower than the prescribed Target Energy Rating (TER) for the specific building type, calculated using a Simplified Building Energy Model (SBEM). However, this methodology does not aim to predict the actual energy consumption of a building, as its purpose is solely to ensure compliance with Building Regulations. Instead, detailed Dynamic Simulation Models (DSMs) can be used to obtain predictions of in-use energy performance. DSMs are more suited to the functional and volumetric complexities of non-domestic buildings as they allow for more detailed input options whilst also containing extensive databases for materials and systems (Raslan et al., 2009). Despite these and many other added capabilities, there is still a significant gap between predicted and actual energy consumption in non-domestic buildings (Bordass et al., 2004). This discrepancy is commonly referred to as the 'performance gap'.

1.1 Performance Gap

The PROBE studies (Post-occupancy Review of Buildings and their Engineering) investigated the performance of 23 buildings previously featured as 'exemplar designs' in the Building Services Journal (PROBE, 2011; Bordass et al., 2001). The research project ran from 1995 to 2002, highlighting the lack in feedback regarding the actual performance of buildings. It also brought to light the so called 'performance gap', suggesting that actual energy consumption in buildings will usually be twice as much as predicted (Bordass et al., 2001). More recently, initiatives such as the Low Carbon Buildings Accelerator and the Low Carbon Buildings Programme, have aimed to provide feedback regarding the performance of buildings in-use (Carbon Trust, 2011a). Findings from both these studies have been published by the Carbon Trust in a series of reports, with one dedicated solely to the performance gap (Carbon Trust, 2011b). The report entitled 'Closing the Gap' introduces the underlying causes of the performance gap, highlighting that design predictions for regulatory compliance do not account for all energy uses in buildings. Data from five case study buildings is used to illustrate the discrepancies between actual regulated energy consumption and modelling output used for compliance with Building Regulations. Results demonstrate that the actual regulated consumption can be five times higher than predicted (Carbon Trust, 2011b).

In 2008, the Royal Institute of British Architects (RIBA) and the Chartered Institution of Building Services Engineers (CIBSE) launched CarbonBuzz, a free online platform allowing practices to share and publish building energy consumption data anonymously (CarbonBuzz 2011). It enables designers to compare predicted and actual energy use for their projects, whilst also allowing for comparison against benchmarks and data supplied by other participating practices. Figure 1 illustrates the predicted and actual electricity consumption in three building sectors: schools, general offices and university buildings (Hamilton et al., 2011). The graph depicts the median predicted and median consumption for the buildings within the database, which are assumed to be broadly representative of each sector. As shown, the measured electricity demands are approximately 60% to 70% higher than predicted in both schools and general offices, and over 85% higher than predicted in university campuses.

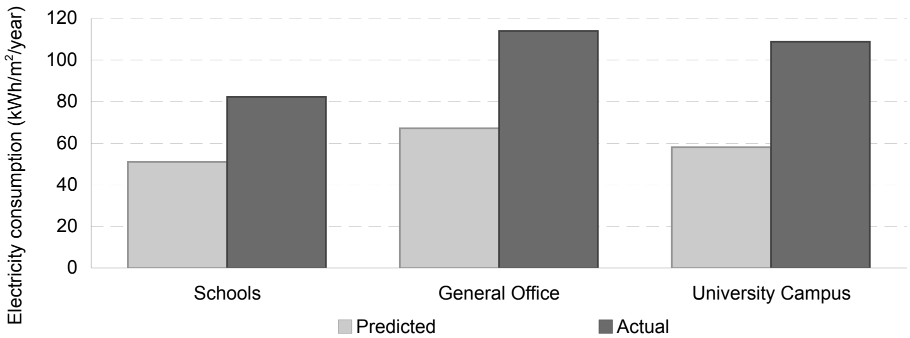

Figure 1: CarbonBuzz median energy use per sector - Predicted vs. Actual

1.2 Sources of discrepancies

Results from the PROBE studies suggest that such discrepancies transcend the expected shortcomings of current modelling programs; being a result of poor assumptions, as well as a lack of monitoring following construction (PROBE, 2011; Bordass et al., 2004). Table 1 summarises the main causes of discrepancies between predicted and actual energy performance in buildings.

As shown, the causal factors relate to both predictive and in-use performance, implying that current predictions tend to be unrealistically low whilst actual energy performance is usually unnecessarily high. However, the overall problem could be interpreted as an inability of current modelling methods to represent realistic use and operation of buildings. This in turn can be associated with the lack of feedback regarding actual use and operation of buildings as well as the resulting energy consumption. Currently, there is a significant lack of information concerning the actual energy performance of our existing building stock (Lowe, 2010). A continued absence of such data is likely to lead to a progressive widening of the gap between theory and practice and a failure to achieve strategic goals (Oreszczyn et al., 2010).

Recent developments in the field of thermal modelling have resulted in increasingly complex simulation software based on calculations of dynamic heat transfer. In addition, stringent procedures are being implemented to ensure the validity of a range of modelling programs (De Wit, 1995). As a result, the impact of modelling tools on the overall discrepancy between predicted and actual performance is consistently being diminished. Meanwhile, some issues with built quality are slowly being tackled by the construction industry, encouraging more airtight buildings and better construction techniques. Extensive research on the actual performance of built elements is also being conducted, whilst most modelling software now allow for assumptions regarding the built quality of specific building elements.

Table 1: Causes of discrepancies between predicted and actual energy performance.

	Causal factors
Predicted Performance	Design Assumptions The input of data into a building energy model relies significantly on assumptions, which often go unchallenged. These are usually made at design stage when many aspects of the building's function and use are unknown or uncertain. This can result in oversimplified and/or unrealistic inputs regarding the built quality and fabric performance, occupancy patterns and behaviour as well as the management and control of the building and its services (De Wit, 1995).
	Modelling Tools Building energy modelling software can contain fundamental errors embedded in the equations used by the program, leading to inaccuracies in the predictions. This should be avoided by choosing modelling tools that have been appropriately validated according to the procedures defined by CIBSE TM33 (CIBSE, 2006b). The choice of software should also consider the specific type of building being modelled and should allow for adequate representation of the building itself as well as its use and operation. Restrictive or oversimplified tools can result in models that are unrepresentative of reality (De Wit, 1995).
Actual Performance	Management and Controls Facilities managers have control over central plant equipment, accounting for a great portion of the energy consumption in a building (especially in highly automated buildings). Good management and controls can result in an efficient operation of the building services whilst inappropriate strategies can result in unnecessary waste of energy (Bordass et al., 2001). Frequent energy audits as well as re-commissioning exercises can help maximise the efficiency of building services, avoiding unnecessary energy waste (Way and Bordass, 2005).
	Occupancy Behaviour Building occupants do not always have direct control over building services such as heating and cooling, yet even in highly automated buildings, occupants can affect their energy consumption by influencing the internal conditions (e.g. opening windows, blocking air inlets/outlets, etc) (Demanuelle et al., 2010). Moreover, occupants have control over various energy consuming equipment and appliances, commonly referred to as 'unregulated loads' (i.e. not controlled by Building Regulations).
	Built Quality The in-use energy performance of a building is affected by the quality of its construction. Issues such as gaps in the insulation and thermal bridging are common, but are rarely considered in the predictions of energy consumption. Moreover, changing requests from clients and/or value engineering exercises can result in significant deviations from what was originally specified (Bordass et al., 2004). Yet these alterations are rarely fed back into the energy model.

Despite these improvements, current simulation tools do not accurately model the impact of occupants and management on the energy performance of buildings. This is usually attributed to the use of inadequate assumptions at design stage, more so than an inability of the modelling tools themselves. As such, there is scope for further investigation into the actual use of buildings, focusing on occupancy and management behaviour, as well as their impact on unregulated energy consumption. This can be achieved through the practice of Post-Occupancy Evaluation (POE).

1.3 Post-occupancy evaluation

Post-Occupancy Evaluation (POE) is a structured process of evaluating the performance of a building after it has been built and occupied. This is achieved through systematic data collection, analysis and comparison with explicitly stated performance criteria, providing designers with valuable information regarding the in-use performance of their designs (Preiser et al., 1987). The scope of POE can be divided into three strands (Cooper, 2001):

- Feedback: a management aid mechanism aimed at measuring building performance mostly as an indicator of business productivity and organisational efficiency.
- Feed-forward: aims at improving building procurement through the use of acquired data as feedback to the design team and future briefings.
- Benchmarking: aims at measuring progress striving towards increasingly sustainable construction and stricter targets of energy consumption.

POE can take several approaches, varying from highly technological methodologies involving hard data, to socio-psychological interests where more subjective parameters are used to evaluate the performance of a building. Hence, the method to be undertaken in a POE is usually defined by the objectives being pursued and the areas of interest to the stakeholder. Seeing as POE concerns the analysis of individual buildings, the methods vary in scale, type, level of interactivity and suitability for specific projects (Turpin-Brooks and Viccars, 2006). As a consequence, a vast number of POE methods and techniques are available worldwide, allowing for an array of different evaluations to be performed in numerous types of buildings.

One of the most widely recognised tools for evaluating the energy performance of buildings in the UK is the Energy Assessment and Reporting Methodology (EARM). Originally developed for the PROBE studies, it was later published by CIBSE as a technical memorandum (CIBSE TM22). The document describes a method for assessing the energy performance of an occupied building based on metered energy use, and includes a software implementation of the method. It can be used to identify poorly performing buildings and systems, indicating the causes of poor performance and benchmarking procedures (CIBSE, 1999). Figure 2 illustrates the underlying structure of the TM22 methodology, depicting the breakdown of energy consumption by end-uses (such as lighting and ventilation) whilst highlighting the impact of low-level factors such as hours of use and equipment efficiency.

The first edition of TM22, published in 1999, consisted of 3 stages:

- Stage 1: A quick assessment of the energy consumption, breaking it down into use per unit floor area and can be carried out by in-house resources. Information required includes description of the building, floor area and annual consumption records.
- Stage 2: A more detailed assessment of the energy consumption including special energy uses or occupancy and can usually be carried out in-house. Information required includes details of building occupancy and usage as well as any special or unusual uses.

- Stage 3: A full understanding of the performance of the building and its systems, and will usually require a specialist to carry out the assessment. Required information includes building operation and maintenance manuals as well as details of building occupancy, use and cleaning, plant operation procedures and schedules.

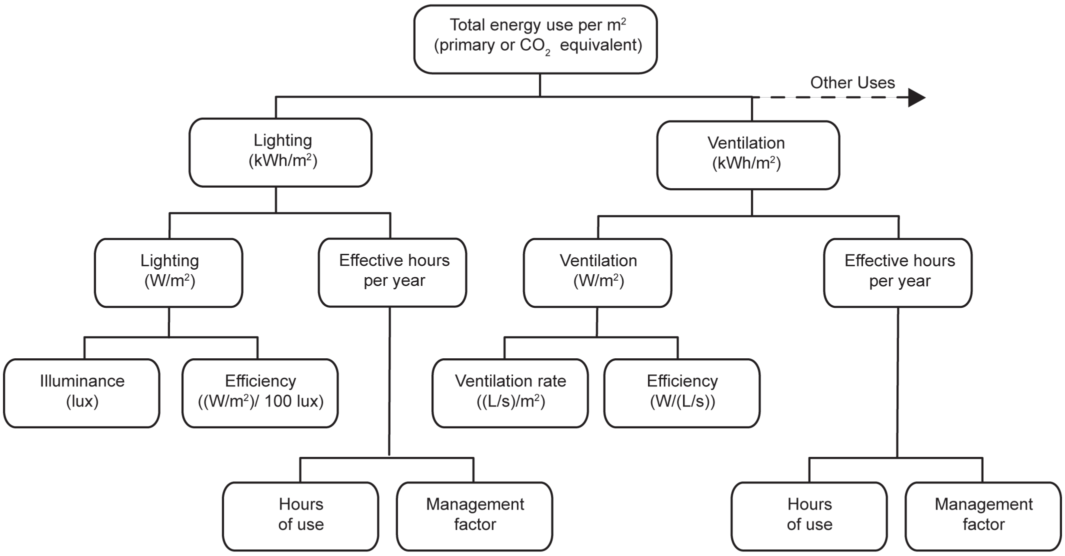

Figure 2: TM22 'Energy Tree Diagram' illustrating the breakdown of energy use.

In 2006, a second edition of the TM22 was published, updating the previous edition by describing procedures for compliance with emerging energy performance legislation (CIBSE, 2006a). It also included treatment of on-site energy generation and renewable energy sources. Overall, it provided a simpler and more effective method for energy assessment and reporting, whilst keeping up to date with current developments in the construction industry. An updated version of TM22 is currently being developed and will be used as a guidance framework for the Technology Strategy Board's Building Performance Evaluation programme (TSB, 2011). This government-funded programme is anticipated to be the largest POE study ever to be conducted in the UK, evaluating the in-use performance of both domestic and non-domestic buildings. One of the key objectives of the programme is to assemble a substantial body of data for a variety of building types, aiming to draw conclusions on the in-use performance of various design strategies. These will be disseminated across the industry to enable improvements in the performance of new and refurbished buildings through better design, delivery and operation.

2 METHODOLOGY

Taking a case study approach, this paper analyses the energy performance of an office building in central London. The assessment was guided by the TM22 methodology, followed by in-depth monitoring of the electricity consumption for lighting, small power and catering equipment. Monitoring of occupancy patterns were also conducted via half-hourly walkthrough inspections. Results from the monitoring exercise were then fed into energy models, aiming to produce more accurate predictions of energy consumption. These focused solely on tenant electricity consumption, excluding all gas usage as well as electricity consumption for air conditioning, ventilation, lifts, water heating and circulation, as well as lighting in communal areas.

2.1 Building Description

The selected building accommodates the offices of four different companies throughout its seven floors and basement. It includes an atrium that extends to all floors (except the basement). Each floor comprises a main open-plan office space with a treated floor area of approximately 2,000m^2. The ground floor houses a large reception area and the basement houses meeting rooms and cellular offices. The building is fully air-conditioned, three rooftop air-handling units (AHUs) provide heating/cooling as well as fresh air to all floors and atrium. A separate system provides heating for the basement, whilst fan coil units (FCUs) provide cooling to the meeting rooms and small individual offices. Two gas-fired boilers provide hot water to all toilets and kitchens throughout the building.

Figure 3 illustrates the metering strategy for the supply of electricity and gas to the building. As shown, the landlord is responsible for the electricity consumed by all air conditioning equipment including the AHUs, FCUs, chillers, pumps and fans as well as the Building Management System (BMS) and other control equipments. The lighting throughout the common areas of the building as well as the toilets is also supplied and maintained by the landlord. As such, the energy supplied for the landlord services is metered together, with no sub-metering for individual end-uses. Meanwhile, the electricity supplied to the tenants for lighting, small power equipment and catering in each of the floors is metered separately. A total of 32 sub-meters provide a further breakdown for each of the 4 zones in each floor: North-East (NE), Northwest (NW), Southeast (SE) and Southwest (SW).

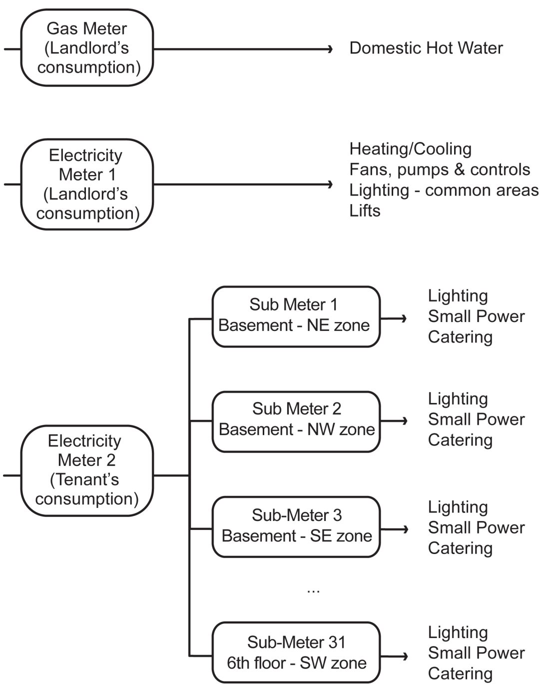

Figure 3: Metering strategy for the supply of gas and electricity to the building.

2.2 Monitoring Process

Following a full TM22 assessment of the building, whereby the total energy consumption for both gas and electricity was analysed and broken down by individual end-use, a further analysis of the tenants' consumption was undertaken. This in-depth study focused on the electricity consumption for lighting, small power and catering within each of the tenant zones, relying on monthly meter readings for each of the sub-meters as well as half hourly profiles acquired through the use of 3-phase portable data loggers connected to the individual sub-circuits. Further data was acquired using combined plug monitor / loggers connected to individual small power office equipment such as laptops, computer screens and printers. These were also used to monitor the electricity consumption of catering equipment such as fridges, microwave ovens and coffee machines. Half hourly profiles for each of the pieces of equipment being monitored were reviewed in order to obtain an average daily consumption value. Where different usage modes were present (such as stand-by mode), these were recorded separately and accounted for when calculating the average daily consumption for each equipment. Occupancy patterns were also monitored by manually recording the number of occupants within the office in half-hour intervals.

3 MONITORING RESULTS

Figure 4 illustrates the annual tenant electricity consumption per floor (normalised by m^2). This includes lighting, small power and catering equipment loads. It is worth noting that the lighting specification and controls are consistent throughout the entire building and the catering facilities in each floor are of a similar size and nature (consisting mainly of an instant hot water heater, a microwave, a dishwasher and a full size fridge). Some floors have additional coffee machines and/or vending machines, and the tenants on the ground floor have a large bar with multiple fridges. In regards to small power, a fairly consistent volume of office equipment is present throughout the building. Despite their different nature of work, all 4 tenant companies have similar occupation densities and office equipment specifications. Most workstations consist of a computer screen, laptop or desktop as well as a phone. Some workstations have individual desk lamps, personal fans and/or desktop printers. In addition, all floors have large printer/copiers (typically 6-8 per floor) as well as projectors and/or flat screen displays in meeting rooms.

As seen, the 2nd floor consumes approximately 60% more electricity per m^2 than the lowest consumer (5th floor). This is quite a significant variation considering the consistency in lighting specification and controls as well as the similarities in installed equipment and occupation density. However, when relating the electricity consumption to the tenants occupying each of the floors, a clearer pattern can be observed. Figure 5 illustrates how the different tenant companies are located throughout the building. As shown, the lowest consuming floors (5th and 6th) are wholly occupied by Tenant C. Similarly, the 3rd and 4th floors are mainly occupied by Tenant B, presenting similar annual consumption values.

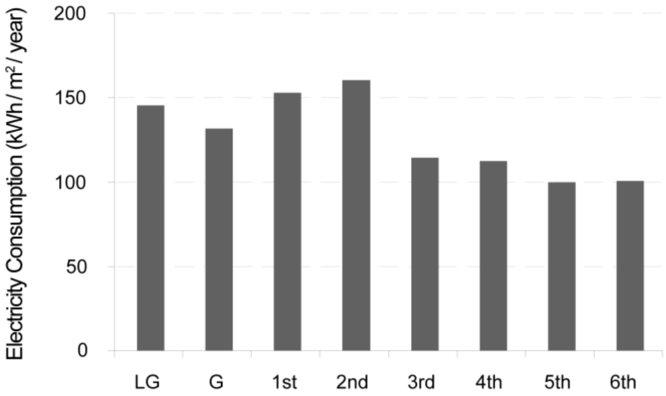

Figure 4: Annual tenant electricity consumption per floor area.

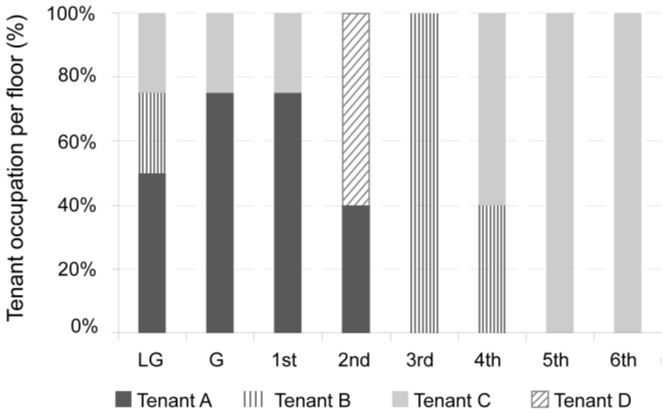

Figure 5: Location of tenant companies throughout the building.

Figure 6 illustrates the annual electricity consumption of each tenant per m^2 of office space they occupy. Not surprisingly, Tenant C has the lowest electricity consumption at 90 kWh/m^2. Tenant A has the highest annual consumption at 155 kWh/m^2, followed closely by Tenant D at 139 kWh/m^2. This might explain why the 2nd floor has the highest consumption seeing as it is occupied by both Tenants A and D.

Figure 6: Annual electricity consumption per tenant (normalised by floor area).

An informal interview was conducted with the facilities co-ordinator of each tenant to investigate the causes of such variations. This revealed that the employees of Tenant A are instructed to leave their computers on overnight for IT upgrades. As such, a large quantity of electricity is used outside the normal operating hours of the building, accounting for a significant portion of their overall consumption. Similarly, employees of Tenant D often leave their computers on at the end of the day so that time-consuming tasks, such as high quality rendering, can be performed overnight. On the other hand, employees of Tenants B and C are heavily encouraged to save energy through internal communications to turn off their computers and screens at the end of the day. Tenant B has also instructed their facilities co-ordinator to switch off printer/copiers and non-essential catering equipment such as coffee machines at the end of each day.

3.1 Detailed Analysis of Electricity Demand

Following the analysis of annual electricity consumption data, an in-depth study was undertaken to examine the variation in electricity demand throughout a typical week. Figure 7 illustrates the half hourly electricity consumption for a single zone in the 4th floor of the building (occupied by Tenant B).

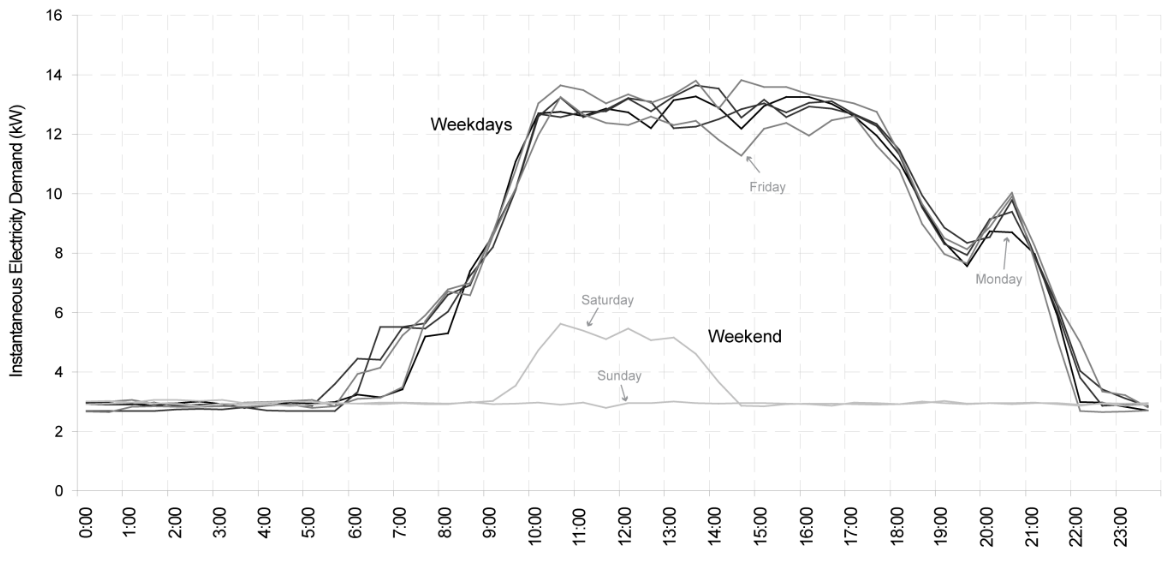

Figure 7: Monitored electricity consumption for 4th floor – Northeast zone.

As shown, the base load is approximately 3 kW outside working hours. The electricity demand starts to escalate around 06:00 peaking at approximately 13 kW by 10:00. This can be associated with the arrival of employees who trigger the motion sensors, turning on the lights. This will usually be followed by office/catering equipment being turned on. From 10:00 to 17:00 the demand remains fairly high, varying between 11-14 kW, eventually decreasing to approximately 8 kW by 19:30. This can be associated with equipment being turned off as employees leave the office. A steep rise in the demand is then observed at approximately 20:30, followed by a fairly quick decrease, bringing the demand down to the base load at around 22:00. This late peak can be associated with the cleaning schedule of the building. It is assumed that the rise in demand is due to the use of vacuum cleaners as well as the dishwasher being turned on. The electricity demand during the weekend is fairly constant at a similar base load to the evenings. The only deviation occurs on Saturday between 9:00 and 15:00 when the electricity demand rises to approximately 5 kW. This can be associated to individual employees going into the office to work extra hours.

The analysis of half hourly electricity consumption has suggested a correlation between occupancy hours and electricity consumption. In order to determine the extent of this correlation, real occupancy levels were monitored and plotted against the half hourly electricity consumption. Figure 8 illustrates the results of this monitoring showing occupancy patterns on a typical working day. As shown, the electricity demand follows the monitored occupancy profile quite closely. The initial peak in demand is observed around 08:00 when occupancy numbers start to increase rapidly. Similarly, a steep decrease in electricity demand is observed after 17:30 when occupancy starts to decrease. However during lunchtime, the quick decrease in occupancy is not reflected in the electricity demand. This is because most computers are kept on and lighting levels remain constant. As previously mentioned, the sharp peak around 20:00 is associated with cleaning.

Figure 8 also illustrates the standard occupancy profile for offices used by SBEM for compliance predictions. Despite its simplistic nature, standard profiles such as this are normally used in DSMs. As shown, there is little correlation between the SBEM profile and the monitored electricity consumption. The impact of using a standard occupancy profile in predictive models is discussed in further detail below.

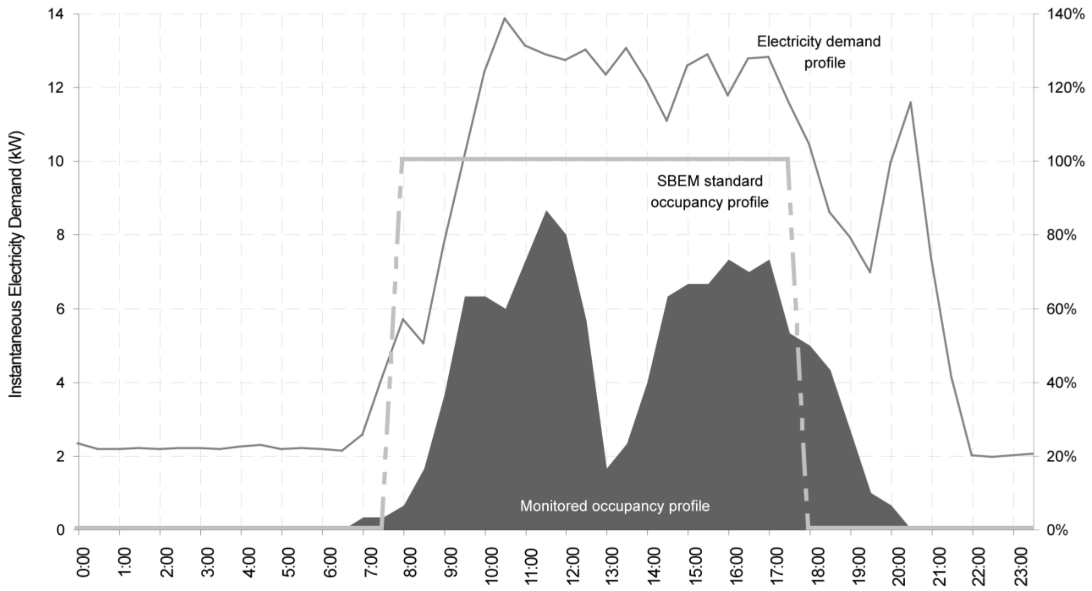

Figure 8: Relationship between monitored electricity consumption and occupancy profiles.

4 PREDICTIVE MODELS

Following the detailed analysis of electricity consumption in the 4th floor NE zone, the acquired data was used to produce 5 predictive models of electricity consumption. These predictions refer to the annual electricity consumption for lighting, small power and catering for this specific zone, occupied by Tenant B. An increasing level of detail was used in each subsequent model, replacing typical assumptions with monitored data. The parameters used for each of the electricity demands are detailed in Table 2. It is worth mentioning that due to increasing complexities in the input parameters of small power and catering equipment, a spreadsheet approach was taken to predict annual electricity consumption. Although most DSMs will allow such detailed parameters to be used, the process of doing so can be quite onerous. In addition, most DSMs rely on a 'black box' approach, meaning that the user has no control over how the calculations are carried out (White and Holmes, 2009), making it difficult to visualise the impact of such detailed inputs in the overall electricity consumption of the building. As such, a bottom-up approach to CIBSE TM22 was used to produce the predictive models. This methodology (illustrated earlier in Figure 2) has previously been used to predict electricity consumption (Bordass et al., 2004; Cohen and Bordass, 2006), allowing for detailed parameters such as load and usage factors to be used. This approach was used in predictive models 1 and 2. Alternatively, metered data can be used to replace assumptions, increasing the accuracy of the model. This approach was used in models 3, 4 and 5, where increasing amounts of data acquired from the monitoring study (mostly through the use of plug monitors) was used to replace standard assumptions regarding energy consumption of specific equipment. Information gathered through the monitoring of occupancy patterns was also used to substitute standard occupancy hours in model 5.

It is worth mentioning that the actual electricity consumption value displayed in Figure 9 was unknown at the time these predictive models were developed. The author was aware of the average consumption per m^2 for Tenant B but did not have access to the actual consumption value for the specific zone being modelled.

Results from the predictive models are illustrated in Figure 9. The predictions are labelled 1-5 accordingly and reflect the inputs specified in Table 2. As seen, the predictions are compared against the actual electricity consumption, which is not subdivided into the specific end-uses due to the limitations of the sub-metering strategy of the building. Two benchmark values are also illustrated in the graph for further comparison. These were acquired from 'Energy Consumption Guide 19' (commonly referred to as ECG19) and illustrate industry benchmarks for Typical (TYP) and Best Practice (BP) energy consumption for lighting, small power and catering in standard air conditioned office buildings with floor areas between $2000m^2$ and $8000m^2$ (i.e. Type 3) (BRECSU, 2000).

Table 2: Input parameters used in each predictive model.

	Brief description	Lighting	Small Power	Catering
1	Typical compliance model using lighting specification from the design brief, using SBEM standard occupancy hours and overlooking small power and catering equipment.	11 W/m^2 2600 hrs/year	Not considered	Not considered
2	'Enhanced' compliance model using industry rules of thumb to account for small power loads (BSRIA, 2003), but overlooking catering equipment.	11 W/m^2 2600 hrs/year	15W/m^2 2080 hrs/year (due to 80% usage factor)	Not considered
3	Initial bespoke model using monitored data regarding the installed lighting load as well as measured electricity demand for basic small power and catering equipment. SBEM standard occupancy hours were used accounting for an 80% usage factor of small power equipment.	13 W/m^2 2600 hrs/year	170 laptops 170 screens 5 printers = 11 W/m^2 2080 hrs/year	1 water heater 1 fridge = 0.3 W/m^2 2600 hrs/year
4	Intermediate bespoke model using monitored data for lighting as well as measured electricity demand for all small power and catering equipment installed. SBEM standard occupancy hours were used once again with allowances for usage factor of small power equipment.	13 W/m^2 2600 hrs/year	170 laptops 170 screens 5 printers 8 desk lamps 6 desk fans = 11.5 W/m^2 2080 hrs/year	1 water heater 1 fridge 1 microwave 1 dishwasher 2 coffee machines = 1 W/m^2 2600 hrs/year
5	Advanced bespoke model using monitored data for lighting as well as measured electricity demand for all small power and catering equipment installed. Monitored hours of use were used for all lighting, small power and catering equipment.	13 W/m^2 3640 hrs/year	170 laptops 170 screens 5 printers 8 desk lamps 6 desk fans = 11.5 W/m^2 [monitored hours of use per individual equipment]	1 water heater 1 fridge 1 microwave 1 dishwasher 2 coffee machines = 1 W/m^2 [monitored hours of use per individual equipment]

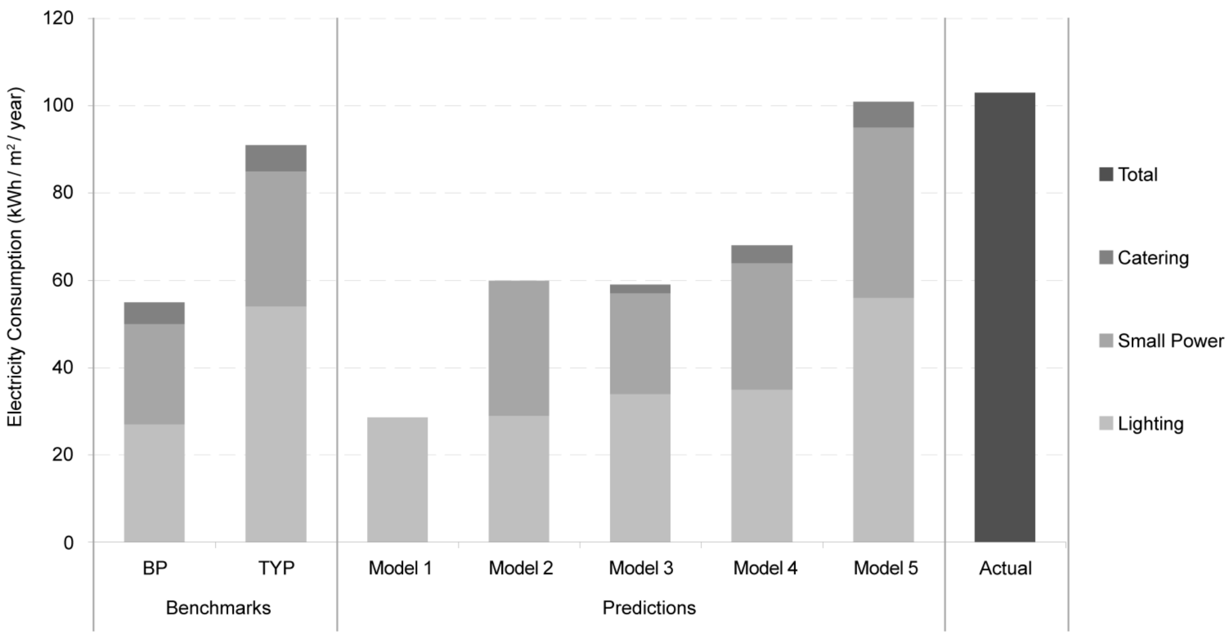

Figure 9: Comparison of benchmarks, predicted and actual electricity consumption.

As shown in Figure 9, the increased detail in the input parameters of models 1-5 have resulted in incremental increases of the predicted annual electricity consumption. By using a typical compliance model in prediction model 1, the calculated electricity consumption was shown to be less than 1/3 of the actual in-use consumption. The predicted value was then increased significantly in prediction model 2 when 'rules of thumb' published by the Building Services Research and Information Association (BSRIA) for small power consumption were used to account for the electricity demand of office equipment (BSRIA, 2003). It is worth mentioning that such rules of thumb are commonly used in DSMs when trying to predict energy consumption of buildings in-use (Dunn and Knight, 2005). In prediction model 3, design specifications and rules of thumb were replaced by monitoring data of installed lighting and equipment. At this point however, only basic equipment were considered and SBEM standard occupancy hours were assumed. This resulted in a similar total prediction of electricity consumption, yet this total consisted of higher lighting loads and lower small power loads. This demonstrates that actual installed lighting loads were higher than specified at design stage. Meanwhile the small power prediction seems to have been fairly conservative by having considered only basic office and catering equipment. In prediction model 4, all installed equipment were included, resulting in an increase of approximately 15% in the total electricity consumption. Finally, in prediction model 5, the SBEM standard occupancy hours were replaced by monitored occupancy hours. By doing so, the predicted electricity consumption came within 3% of the actual consumption of the building in-use. This small discrepancy could be associated with the fact that the predictions were based on measurements from a single day. As such, the model assumes a typical operation throughout the entire year, disregarding variations in both occupancy and energy use profiles that are bound to occur.

When comparing the results from the predictive modelling against the ECG19 benchmarks, it is possible to conclude that the final prediction is only slightly higher than the typical benchmark for a Type 3 office building. However, when considering that Tenant B had the second lowest consumption per m^2 in the building, one would expect it to be lower than the typical benchmark and perhaps closer to best practice. Considering that the ECG19 benchmarks were compiled over 10 years ago, they might not be representative of current office buildings. With the fast advancements in the design of low energy ICT equipment, energy consumption due to small power would be expected to have decreased in the last decade. However, current offices are now run for longer hours and tend to contain more items of small power equipment. The same would be expected for lighting and catering, resulting in similar proportions of electricity being consumed by each end-use. The lack of more up-to-date benchmarks makes it hard for further conclusions to be drawn.

4.1 Methodology Validation

In order to validate the methodology used to generate the predictive models, the same approach was used to model another zone in the building occupied by a different tenant (i.e. 2nd floor South-West zone occupied by Tenant D). Once again a walk through inspection was undertaken to determine the quantities of installed equipment throughout the zone. Plug monitors were then used to log the energy consumption of different small power and catering equipment, and variations in occupancy density were also monitored via half-hour inspections throughout the day. Acquired data was incrementally used to inform the input parameters for the predictive models, as detailed in Table 3.

Table 3: Input parameters used in predictive models for methodology validation

	Lighting	Small Power	Catering
1	11 W/m^2 2600 hrs/year	Not considered.	Not considered.
2	11 W/m^2 2600 hrs/year	15 W/m^2 2080 hrs/year (due to 80% usage factor)	Not considered.
3	Fixed lighting =12.8 W/m^2 2600 hrs/year	40 laptops 70 desktops 110 screens 4 printers = 11.6 W/m^2 2080 hrs/year	1 water heater 1 fridge = 0.3 W/m^2 2600 hrs/year
4	Fixed lighting plus decorative and task lighting = 17.3 W/m^2 2600 hrs/year	40 laptops 70 desktops 110 screens 4 printers 2 desktop printers 3 plasma TVs = 12.6 W/m^2 2080 hrs/year	1 water heater 1 fridge 3 glass front fridges 2 microwave 1 dishwasher 2 coffee machines 2 vending machines = 2.3 W/m^2 2600 hrs/year
5	Fixed lighting plus decorative and task lighting = 17.3 W/m^2 3120 hrs/year	40 laptops 70 desktops 110 screens 4 printers 2 desktop printers 3 plasma TVs = 12.6 W/m^2 [monitored hours of use per individual equipment]	1 water heater 1 fridge 3 glass front fridges 2 microwave 1 dishwasher 2 coffee machines 2 vending machines = 2.3 W/m^2 [monitored hours of use per individual equipment]

The previous investigation into the energy use of Tenant D had revealed that a significant proportion of employees routinely left their computer on overnight in order to run time consuming tasks. In order to account for this behaviour into the predictive models, an assumption was made that 20% of computers were constantly left on. This assumption was made based on rough estimated provided by Tenant D's IT technicians. Figure 10 compares the results of the predictive models with the actual electricity use for the zone being analysed. It also illustrates the results from the previous predictive models for the zone occupied by Tenant B.

As seen in Figure 10, the first two models are identical for both zones. This is due to the fact that they are compliance models, which do not account for actual installed loads or any specific characteristics of the individual zones. Models 3 – 5 provide increasing levels of detail into the installed equipment within each of the zones, progressively increasing the accuracy of the models. Once again it is the final step of adjusting the occupancy hours that seems to have the highest impact towards achieving an increasingly accurate prediction.

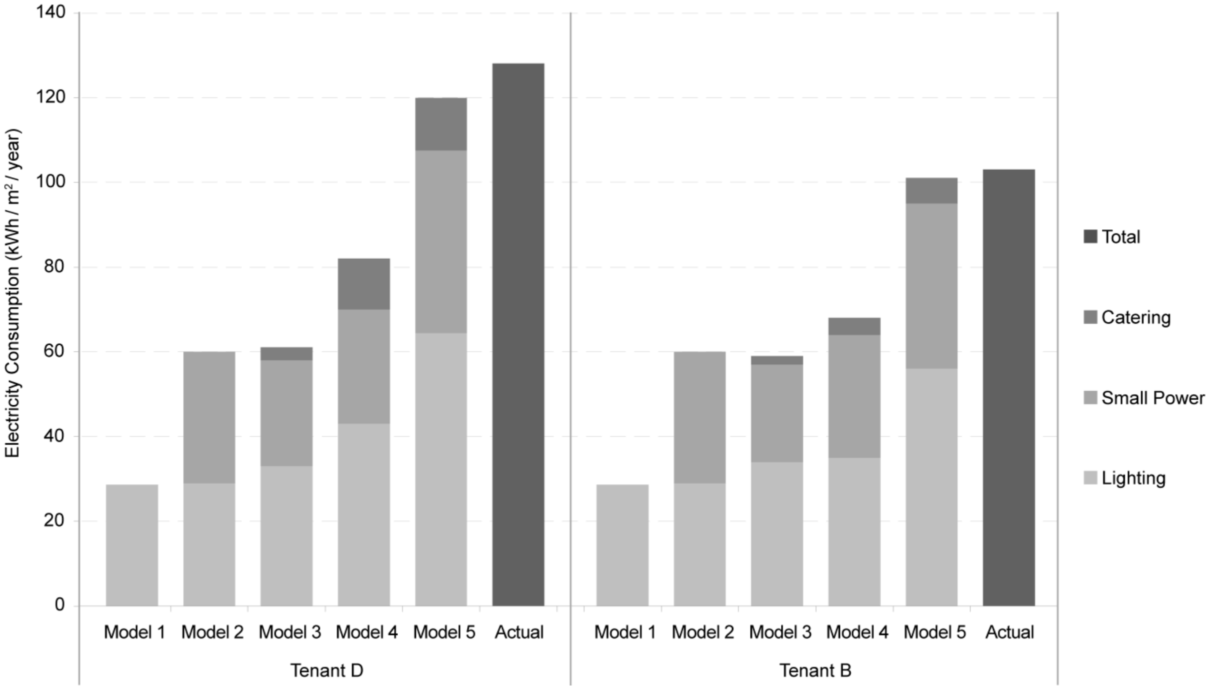

Figure 10: Predictive model results and actual electricity consumption in both zones investigated.

During this validation exercise, the final model achieved a prediction within 6% of the actual electricity consumption of the zone, being slightly less accurate than the initial set of predictive models. This could be related to the assumptions made regarding the proportion of employees who leave their computer on overnight, suggesting that more than 20% of computers are constantly left on overnight. This emphasises the importance of minimising the use of assumptions in order to achieve realistic predictions.

5 CONCLUSION

This paper has discussed the existence of a gap between predicted and actual energy consumption in non-domestic buildings. It has highlighted the main causes of such discrepancies, identifying POE as a key tool for understanding this issue further. It also identified the potential for using POE results to inform predictions, enabling better assumptions to be used in detailed energy modelling. A case study revealed that by conducting basic monitoring exercises it is possible to feed results into energy models and gain a more accurate prediction of a building's actual performance (within 3% of actual consumption for this specific study). A validation exercise demonstrated that replicating the methodology within a different zone in the building produced results within 6% of the actual energy use for the zone. Despite the limited applicability of this methodology to non-speculative buildings, the results are encouraging and demonstrate that reliable predictions can be obtained for lighting and small power loads by using realistic assumptions in the modelling process. It is also worth mentioning that improved predictions for electricity consumption due to lighting and equipment can also inform better assumptions regarding internal loads, which can in turn improve the prediction of cooling and heating demand in a building.

Key findings from this study highlight the need for better understanding of occupancy patterns and behaviour in office buildings. Variations in the electricity consumption of different tenants occupying the same building have demonstrated that modelling software should account for different occupancy patterns and behaviours if realistic predictions are to be achieved. In addition, a clear correlation was observed between monitored occupancy profiles and tenant electricity consumption. It should be noted however, that energy demand can vary largely with tenant behaviour throughout the day (not only when they arrive or leave). The impact of management was not analysed in this study due to its focus on tenant consumption. It is important to highlight, however, that management decisions, such as the running of ICT updates outside of occupancy hours, were observed to have a significant impact on the tenant consumption. Inconsistencies between design specification and installed lighting loads were also observed to have a considerable impact on the discrepancy between predicted and actual electricity use.

If the UK is to experience real reductions in its CO_2 emissions, it is imperative that we start achieving energy efficiency in practice. With Building Regulations relying heavily on predictive indicators of performance, it is vital that we understand the limitations of the current compliance modelling and aim to predict realistic energy consumption levels by using detailed DSMs that account for realistic occupancy and management behaviours. The widespread practice of POE can help us understand how occupants and facilities managers interact with the built environment. It can also provide valuable information regarding the performance of the current building stock.

6 FUTURE WORK

Future work will seek to use detailed POE data to develop a set of evidence based benchmarks for energy consumption in office buildings. It is envisioned that these benchmarks will inform designers regarding the impact of occupancy and management on the actual energy consumption of offices. Moreover, it should enable the use of more realistic input parameters in energy models, bringing the predicted figures closer to reality.

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APPENDIX C BENCHMARKING SMALL POWER ENERGY CONSUMPTION IN OFFICE BUILDINGS IN THE UNITED KINGDOM: A REVIEW OF DATA PUBLISHED IN CIBSE GUIDE F (PAPER 3)

Full Reference

Menezes, A., Cripps, A., Buswell, R., Bouchlaghem, D., 2013. Benchmarking small power energy consumption in office buildings in the United Kingdom: A review of data published in CIBSE Guide F. *Building Services Engineering Research & Technology,* vol.34, no. 1, pp. 73-86.

Abstract

CIBSE's Guide F is a widely recognised guidance document on energy efficiency in buildings, which includes energy consumption benchmarks for small power equipment in offices. In its recently published 3rd edition, existing power demand benchmarks for office equipment were revised to better represent appliances found in contemporary office buildings. Other key sources of data such as typical operating hours for equipment, however, have been omitted. This paper compares the benchmarks published in both the 2nd and 3rd editions of Guide F against a set of measurements of small power loads in a real UK office building. Load profiles for the monitored equipment are also presented to supplement the information included in the new Guide F.

Practical Application

With the increasing demand for more realistic predictions of operational energy use in buildings, small power should not be disregarded since it typically accounts for more than 20% of total energy used in offices. Furthermore, small power loads can have a significant impact on the cooling loads of a building. This paper reviews existing benchmarks, focusing on the new update to CIBSE Guide F, comparing available benchmarks against newly gathered monitored data. Detailed load profiles for individual office equipment are also provided, which can be used by designers to inform better predictions of small power consumption in office buildings.

Keywords – Small power, appliances, offices, energy performance, performance gap

Paper type – Journal Paper

1 INTRODUCTION

There is significant pressure to continue to improve the energy performance of buildings. A critical part of the design process is to be able to make realistic predictions of the energy performance in-use, however studies have demonstrated that buildings typically consume significantly more energy than anticipated (Bordass et al., 2004; Bordass et al., 2011; Menezes et al., 2012). This so-called 'performance gap' can be attributed to numerous factors relating to model based predictions as well as building operation. A key factor in the UK is the exclusion of several sources of energy use from the compliance calculations for Part L of the Building Regulations. These include all small power equipment, as well as external lighting, vertical transportation and ICT servers. In an office building, small power loads will typically represent a large proportion of the total energy consumption, with office equipment alone accounting for more than 20% of the total energy use (BRECSU, 1997). Data from Energy Consumption Guide (ECG) 19 provides typical and good practice values for office equipment and catering electricity conusmption, depicted in Figure 1, labelled 'TYP' and 'GP' respectively (BRECSU, 2000). Values for four different types of office buildings are given: 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).

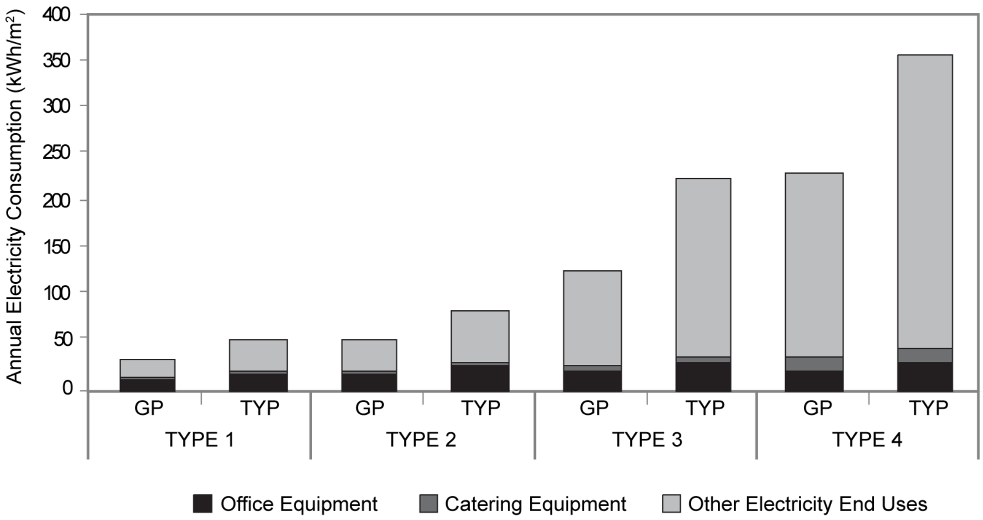

Figure 1: Typical and best practice electricity consumption for office equipment and catering equipment in office buildings (BRECSU, 2000)

According to ECG19, electricity consumption for office equipment ranges from 12 kWh/m^2 per year for good practice Type 1 offices, to 32 kWh/m^2 per year in typical Type 4 offices (BRECSU, 2000). These values respectively represent 36% and 9% of the total electricity consumption in each office type. The annual electricity consumption for catering equipment typically ranges from 2 kWh/m^2 per year to 15 kWh/m^2 per year, accounting for 6% to 4% of the total electricity consumption, respectively. Combined, office equipment and catering will usually represent between 13% and 44% of the total electricity consumption in an office building. These are significant proportions of the total building electricity load and should be given more attention if realistic predictions are to be achieved.

According to the British Council for Offices (BCO), there is significant difference between actual small power loads observed in occupied buildings and those assumed for design purposes (BCO, 2009). The BCO also claims that current benchmarks fail to account for diversity of use, highlighting a need for more detailed benchmarks that reflect current and realistic usage of small power equipment in office buildings. Aiming to address these issues, this paper reviews and assesses the validity of existing benchmarks for small power consumption in office buildings using monitored data acquired as part of a case study. The scope of this review focuses mainly on the widely recognised CIBSE Guide F including its recent update published in May 2012 as well as the widely referenced previous (2nd) edition.

2 EXISTING BENCHMARKS AND CIBSE GUIDE F

One of the most widely recognised guidance documents on energy efficiency in buildings is CIBSE's Guide F (CIBSE, 2004; CIBSE, 2012). Section 12 of the publication deals exclusively with electrical power systems and office equipment, providing a compilation of data regarding power demand and energy consumption for small power equipment. Since the publication of its 2nd edition in 2004, Guide F has provided engineers with a wide range of benchmarks for an array of energy end-uses and building types, compiling information from numerous sources. The scope of this review will cover the key benchmarks published in the 2nd edition of Guide F, which have widely been used by designers over the last 8 years. It will also include a review of updates in the recently published, 3rd edition of Guide F. Data from other sources such as academic papers and reports will also be discussed, providing additional context.

Table 1 displays high-level benchmarks for office equipment, originally published in ECG19 (BRECSU, 2000). The data relates to the 4 office types from ECG19 and provides typical (TYP) and good practice (GP) figures for installed capacity (in W/m^2), annual running hours and percentage ICT area in relation to the treated floor area. In combination these values are used to calculate typical annual energy consumption data for office equipment (in kWh/m^2 per year).

Table 1: Benchmarks for office equipment originally published in ECG19

	Type 1		Type 2		Type 3		Type 4	
	GP	TYP	GP	TYP	GP	TYP	GP	TYP
Installed capacity: floor area with ICT (W/m^2)	10	12	12	14	14	16	15	18
Annual running hours (1000 of hours)	2	2.5	2.5	3	2.75	3.25	3.0	3.5
ICT area as % of treated floor area (%)	60	60	65	65	60	60	50	50
Consumption: office equipment (kWh/m^2)	12	18	19.5	27.3	23.1	31.2	22.5	31.5

According to the 2nd edition of CIBSE Guide F, allowances of 15 W/m^2 for installed loads are adequate for all but the most intensive users (CIBSE, 2004). The same value of 15 W/m^2 is also published by the Building Services Research and Information Association (BSRIA) in their 'Rules of Thumb' guide as a typical small power load in general offices (BSRIA, 2003).

Actual energy consumption data published by the BCO in 2009 suggests that higher installed loads can be found in typical office buildings, with one third of the offices monitored having installed loads higher than 15 W/m^2 (BCO, 2009). With these findings in mind, the 3rd edition of Guide F suggests that a guide figure for building loads of 25 W/m^2 is adequate for most office buildings (with 15 W/m^2 when diversity is taken into account). A previous study by Wilkins and McGaffin (1994) also highlighted the importance of diversity, reporting on monitored energy consumption for small power in five office buildings in the US. Power densities of 18.8 W/m^2 were reported without diversity, decreasing to 8.6 W/m^2 once diversity had been accounted for.

BSRIA's Technical Note 8/92 highlights the risks associated with high level benchmarks for power demand reported in W/m^2. According to the document such values must be considered carefully as there are a number of factors which can influence power demand such as workstation density and space utilisation. This issue is raised in the updated Guide F with a suggestion that designers use a loading of approximately 140–150 W/desk when occupancy details are known.

Numerous other parameters such as power management settings on ICT devices are also not captured by high level benchmarks, yet can have a significant impact on the instantaneous power demand as well as overall energy consumption. In 2003, the Australian National Appliance and Equipment Energy Efficiency Program (NAEEEP) published a report on the operational energy use of office equipment, investigating the impact of different power management settings on the overall energy consumption of desktop and laptop computers as well as monitors (NAEEEP, 2003). The results demonstrated that significant variations in energy consumption occur when different power management settings are applied to the same device. When aggressive power management was implemented (powering down the computer to sleep mode after 5 minutes of inactivity) all machines used approximately 75% less energy than they would have consumed if no power management settings were applied.

Aiming to address such variations, as well as other parameters influencing energy consumption, CIBSE Guide F (both in its 2nd and 3rd editions) provides an alternative methodology for calculating installed loads based on a 'bottom-up' approach. This method was adapted from Energy Consumption Guide 35 (BRECSU, 1993), providing a more robust prediction of energy consumption as opposed to high level benchmarks and relies on numerous sources of information, including:

- list of expected types of equipment;
- typical power consumption figures;
- estimated number of devices;
- proportion of equipment with 'sleep mode' enabled;
- usage diversity; and,
- typical hours of usage for each equipment type.

Table 2 provides values for the typical maximum, average and stand-by power demands for individual office equipment, including data published in both the 2nd and 3rd editions of CIBSE Guide F (CIBSE, 2004; CIBSE, 2012). Most of the benchmarks included in the 2nd edition were originally published in the Building Research Energy Conservation Support Unit's (BRECSU) Good Practice Guide 118 (BRECSU, 1997). Data included in the 3rd edition are based on a combination of five sources including research projects conducted by ASHRAE and the Market Transformation Programme (Hosni and Beck, 2010; DEFRA, 2009).

Table 2: Typical levels of energy used by office equipment published in CIBSE Guide F

Item	Max. rating (W)	Average consumption (W)		Stand-by consumption (W)	
	2nd ed.	2nd ed.	3rd ed.	2nd ed.	3rd ed.
PC and monitor	300	120-175	n/a	30-100	n/a
Personal computer	100	40	65	20-30	6.6
Laptop computer	100	20	15-40	05-10	1.4-4
Monitors	200	80	30	10-15	0.52-1.54
Laser Printer	1000	90-130	110	20-30	10-20
Ink Jet Printer	800	40-80	n/a	20-30	n/a
Printer/scanner/copier	50	20	135	08-10	20-80
Photocopiers	1600	120-1000	550-1100	30-250	15-300
Fax machines	130	30-40	20-90	10	10-15
Vending machines	3000	350-700	n/a	300	n/a

Table 3 details information from the 2nd edition of Guide F regarding typical daily use of office equipment by users as well as the minimum likely staff numbers per machine in large offices, accounting for intermittent usage. This data, however, is excluded from the 3rd edition of Guide F because it has not been updated since its original publication in 1992 in a BSRIA technical note which has now been removed from circulation (Parsloe and Hejab, 2003). Instead, the new Guide suggests that designers acquire the necessary information about the future office functions through discussions with clients and prospective occupiers, rather than relying on rules of thumb.

Table 3: Typical daily use of office equipment and minimum likely staff numbers per machine

Item	Typical daily hours of use	Persons per machine
Personal Computers	4 hours	1
Printers	1-2 hours	3
Photocopiers	1-2 hours	20
Fax Machines	20-30 minutes	20
Vending Machines	8-10 hours	n/a

3 RESEARCH GAP AND PROPOSED INVESTIGATION

Despite the recent update to Guide F, additional information to help designers generate realistic predictions of small power consumption is still lacking in the following areas:

- details of typical hours of use;
- typical number of equipment per m^2 or staff (i.e. installed density); and,
- levels of diversity of use/stand-by;

The availability of data to support the estimation for these parameters is improving. A recent study by Acker et al. (2007) compiled data for small power consumption and load profiles for typical weekday and weekend usage based upon a two year study of 6 different office types from 2010-2012. The study provided useful results for evaluating the typical energy consumption and hours of usage for 'total' small power loads (i.e: at the distribution panel level), also highlighting a wide variance in installed plug load densities. However, the study did not provide load information on an individual appliance basis and so presented in this paper are some results from a monitoring study that includes small power load profiles for individual appliances. Table 4 details the scope of appliances monitored and the representation in both publications of Guide F.

Table 4: Description of data included in the study as well as both editions of Guide F

Item		2nd ed	3rd ed	Monitoring Study	Comments
Laptop Computers		✓	✓	✓	Monitoring included machines with distinctive processing powers
Personal Computers		✓	✓	✓	
Monitors		✓	✓	✓	Monitoring included a variety of screen dimensions
Printer	Laser	✓	✓	×	Not available in the case study office building
	Ink jet	✓	✓	✓	Only one desktop inkjet printer was available for monitoring
Printer/scanner/copier		✓	✓	×	Not available in the case study office building
Photocopiers		✓	✓	✓	Monitoring included 2 machines but of similar specifications
Fax machine		✓	✓	×	Not available in the case study office building
Vending machines		✓	×	✓	Monitoring included hot and cold drinks units
Microwave oven		×	×	✓	Commonly found in office buildings but not included in benchmarks – worthwhile investigating
Fridge		×	×	✓	

A minimum of two appliances were monitored for each equipment type, with the exception of desktop inkjet printers. Class 1 accuracy Telegesis 'ZigBee Plogg-ZGB' plug monitors were used and have a published measurement uncertainty of <0.5%. The power consumption was monitored at 5-minute intervals and aggregated energy consumption was logged every 30 minutes. The findings from the study are compared to the old and new Guide F benchmarks.

4 RESULTS

Figure 2 displays the results from the monitoring study compiled into graphs illustrating the typical weekday load profiles for different equipment. Table 5 highlights key power demand values for stand-by mode, maximum demand and average in-use demand. It is worth noting the 'maximum demand' values relate to the half hourly averages and peaks within this interval are likely to have been higher.

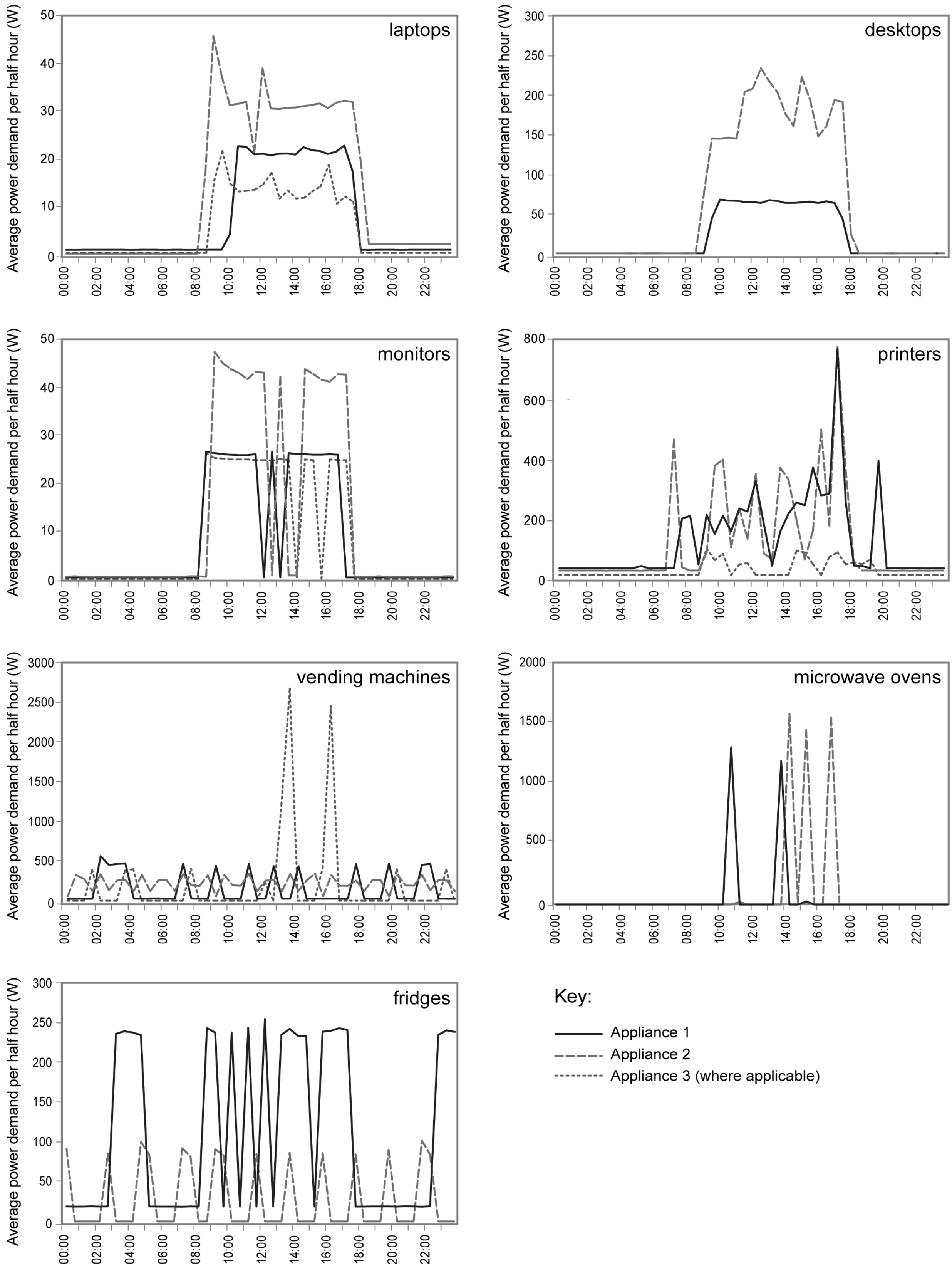

Figure 2. Monitored power demand profiles for each appliance.

Table 5: Key power demand values for each monitored appliance

	Equipment	Appliance 1	Appliance 2	Appliance 3
a	Laptops	1.3 GHz Intel Centrino processor	2.3 GHz Intel Core Duo processors	2.6 GHz Intel Core i5 processors
	Stand-by mode	1.1	0.3	0.5
	Maximum demand	22.9	45.8	27.6
	Average in-use	20.3	30.9	17.9
b	Desktops	2.3 GHz Intel Core Duo processors	3.4 GHz Intel Xeon processors	-
	Stand-by mode	1.9	2.0	-
	Maximum demand	69.1	233.7	-
	Average in-use	64.1	168.6	-
c	Monitors	19” LCD flat screen	19” LCD flat screen	21” LCD flat screen
	Stand-by mode	0.7	0.4	0.8
	Maximum demand	26.7	26.3	47.7
	Average in-use	23.2	22.4	35.7
d	Printers	Large network printer/photocopier	Large network printer/photocopier	Desktop ink-jet printer
	Stand-by mode	37.2	29.9	15.6
	Maximum demand	765.1	771.6	103.0
	Average in-use	223.2	235.1	49.1
e	Vending Machines	Snacks (food)	Cold drinks	Hot drinks
	Stand-by mode	89.0	88.9	23.4
	Maximum demand	623.3	392.6	2663.9
	Average in-use	158.8	262.1	337.8
f	Microwave Ovens	800W power rating	900W power rating	-
	Stand-by mode	2.1	1.9	-
	Maximum demand	1299.7	1578.9	-
	Average in-use	115.8	210.4	-
g	Fridges	Full size fridge (375 L)	Small fridge (150 L)	-
	Stand-by mode	18.0	0.0	-
	Maximum demand	237.8	98.8	-
	Average in-use	133.6	26.4	-

4.1 Laptop computers

Three laptop computers with differing processing powers were monitored as part of this study. Note that values for laptop power demand were obtained while external monitors were being used, i.e. excluding the power demand for the in-built laptop screens. External monitors have been treated separately in the study. The newest laptop (Laptop 3), with an average in-use demand of 17.9W, had the lowest overall power demand, despite its occasional peaks throughout the day. Laptop 1 had an average in-use demand of 20.3W, and a less peaky power consumption throughout the day which was attributed in part to its single processor. Laptop 2 had the highest power demand in-use, averaging 30.9W and reaching a maximum value of 45.8W over 30-minute intervals, more than twice the maximum value recorded for Laptop 1. With regards to stand-by power demand, Laptop 1 consumed the most energy when not in use at 1.1W, compared to Laptops 2 and 3 at 0.3W and 0.5W respectively.

4.2 Desktop computers

Desktop 1 was a 3-year old computer with a 2.3 GHz processor, typically used to run programs such as word processors and spreadsheets. Desktop 2 was a higher performance computer with a 3.4 Ghz multi-core processor used to run 3D modelling software and Computational Fluid Dynamic (CFD) programs. It is worth noting that there were only 6 of these desktops in the monitored office amongst more than 200 computers. Desktop 1 consumed significantly less energy than Desktop 2 with an average in-use demand of 64.1W compared to 168.6W. The power demand from Desktop 1 was fairly constant throughout the working day. The power for Desktop 2, however, fluctuated between 140W - 230W, which might be expected as computationally intensive modelling processes tend to be executed and completed over a certain period. When considering stand-by mode, both desktops consumed similar amounts at approximately 1.9W.

4.3 Computer monitors

All three computer monitors investigated in this study were LCD screens. Monitors 1 and 2 had 19-inch screens and Monitor 3 had a 21-inch screen. All three monitors had power management settings activated: Monitors 1 and 3 switched to stand-by mode after 30 minutes of inactivity; and Monitor 2 had a shorter 'power-down' time of 15 minutes. As seen in Figure 2, the larger monitor consumed almost twice as much energy as the two smaller ones, with a maximum half-hourly demand of 47.7W compared to 26.3W - 26.7W for the 19-inch screens. In stand-by mode, Monitor 2 had the lowest consumption at 0.4W, Monitors 1 and 3 had 0.7W and 0.9W respectively. Monitor 2's shorter 'power-down' time resulted in more frequent drops in energy consumption (to stand-by level) throughout the day resulting in a marginally lower average consumption than Monitor 1, despite their equal screen dimensions and almost identical peak power demand. The significant point here is that if both screens are permanently powered on because of the workload and are off for the same time (i.e. lunch break and overnight) then the power management strategy will have little impact, yet this could be more significant with intermittent use.

4.4 Printers

Three printers were monitored as part of this study: Printer 3 was a desktop ink-jet printer and Printers 1 and 2 were large-scale digital laser printers. The desktop ink-jet printer (Printer 3) had a significantly lower power demand than both large-scale digital printer/scanner/photocopiers, averaging at 49.1W with maximum half-hourly demands of 103W. Printers 1 and 2 had average demands around 230W and maximum recorded demands of approximately 770W. These values reflect the operational characteristics of the desktop and office scale devices in terms of print speed and volume. What is interesting, however, is the relatively high stand-by power demand of Printer 3 at 15.6W when compared to the large machines at 29.9W and 37.2W.

4.5 Vending Machines

Vending Machine 1 sold snacks (such as crisps and sweets) and Vending Machine 2 sold cold drinks, both being refrigerated. Vending Machine 3 sold hot drinks and so contained a water heating device. Vending Machine 3 consumed significantly more energy than Vending Machines 1 and 2 due to its heating element, with an average demand of 337.8W compared to demands of 158.8W and 262.1W, respectively. When considering monitored maximum demands, Vending Machine 3 operated at up to 2,663W, with a maximum half-hourly power demand approximately four times higher than Vending Machine 1 and almost seven times more energy intensive than Vending Machine 2. The load profiles for Vending Machine 3 clearly illustrate peak demands around lunchtime and late afternoon due to increased usage by employees purchasing hot drinks. When considering minimum power demands, the roles were reversed, with Vending Machines 1 and 2 having somewhat higher demands to cope with their cooling functions, demanding at least 57W compared to Vending Machine 1's minimum demand of only 23.4W.

4.6 Microwave Ovens

Both monitored microwave ovens had stand-by consumptions of approximately 2W and similar maximum half-hourly demands of 1,299.7W to 1,578.9W when in use. Microwave 2's higher maximum demands can be associated with its higher power rating at 900W compared to Microwave 1's 800W rating. Such ratings refer to the each oven's capacity to produce microwave radiation and typical energy demand is usually higher due to waste heat production and other inefficiencies. When considering each microwave oven's average energy demand, Microwave 2 demonstrated significantly higher values than Microwave 1, with 210.4W compared to 115.8W, respectively. This can be associated both with the increased power rating and with the fact that Microwave 2 seems to have been used more frequently throughout a typical day than Microwave 1.

4.7 Fridges

Fridge 1 is a large upright unit with a 375litre capacity and Fridge 2 a small upright unit with a 150 litre capacity. Fridge 1 had a consistently higher power demand than Fridge 2, with average and maximum demands of approximately 140W and 240W, compared to 27W and 100W for Fridge 2. When considering the minimum demand, Fridge 2 had a negligible demand, typically 0W, whereas Fridge 1 had a minimum demand of 18W due to the unit having a small freezer.

5 COMPARISON OF MONITORED DATA AGAINST BENCHMARKS

Tables 6-8 display the benchmarks for small power equipment published in the 2nd and 3rd editions of CIBSE Guide F as well as monitoring data discussed above. Figure 3 provides a graphical representation of the data illustrating the values as single data points or ranges in line with the available information. It is worth noting that benchmarks for fridges and microwave ovens are not covered in either edition of Guide F so have not been included here.

Table 6: Benchmarks and monitored maximum energy demand for small power equipment

Item	Maximum demand (W)	
	Guide F 2nd ed.	Monitored
Laptop Computers	100	23-46
Desktop Computers	100	69-234
Computer Monitors	200	26-47
Desktop printers	800	103
Photocopiers	1600	765-772
Vending Machines	3000	513-2664

Table 7: Benchmarks and monitored average energy demand for small power equipment

Item	Average demand (W)		
	Guide F		Monitored
	2nd ed.	3rd ed.	
Laptop Computers	20	15-40	18-31
Desktop Computers	40	65	64-169
Computer Monitors	80	30	22-36
Desktop printers	40-80	135	49
Photocopiers	120-1000	550-1100	223-235
Vending Machines	350-700	n/a	183-338

Table 8: Benchmarks and monitored stand-by energy demand for small power equipment in offices

Item	Stand-by demand (W)		
	Guide F		Monitored
	2nd ed.	3rd ed.	
Laptop Computers	5-10	1.4-4	0.3-1.1
Desktop Computers	20-30	6.6	1.9-2
Computer Monitors	10-15	0.52-1.54	0.4-0.8
Desktop printers	20-30	20-80	15.6
Photocopiers	30-250	15-300	30-37
Vending Machines	300	n/a	23-89

Benchmark data for maximum demand is longer available in the 3rd edition of Guide F, having been replaced by nameplate ratings and so comparisons for maximum demand have been made against the 2nd edition of Guide F only. Benchmarks for vending machines have also been removed in the 3rd edition of Guide F.

5.1 Laptop computers

Maximum monitored demands for laptop computers were observed to be significantly lower than the equivalent benchmarks from the 2nd edition of Guide F, with the highest consuming laptop having a maximum demand of approximately 50% of the benchmark value. The average demand of all monitored laptops, however, had a consumption range that incorporated the old benchmark value and fell within the range of the updated benchmarks published in the 3rd edition of Guide F. Meanwhile, the stand-by loads monitored were significantly lower than the old and new benchmarks, despite the fact that the benchmarks provided in the 3rd edition have been significantly reduced compared to those in the 2nd edition.

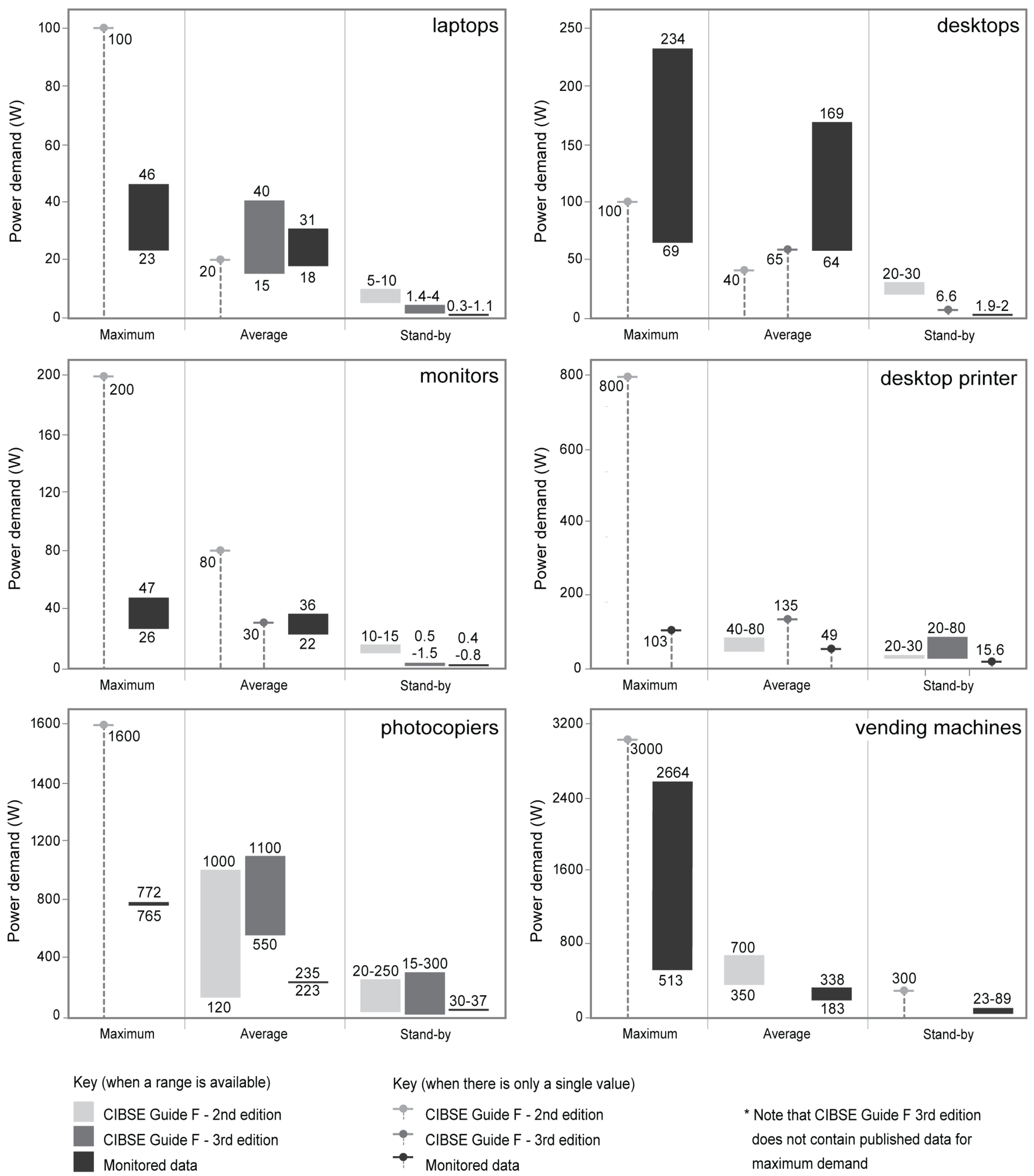

Figure 3. Comparison of benchmarks and monitored power demand for small power equipment in offices

5.2 Desktop computers

A maximum monitoring demand of 234W was observed as part of this study (for Desktop 2), being significantly higher than the maximum rating benchmark of 100W published in the 2nd edition of Guide F. This could present significant problems if high specification desktop computers such as Desktop 2 were to be specified in an office building, resulting in significantly higher internal heat gains than anticipated if these benchmarks were to be used. Both monitored desktop computers consumed more energy than the benchmark published in the 2nd edition of Guide F on average, with the higher specification desktop consuming over four times the benchmark demand (of 40W). Similar findings were reported by Duska et al. (2007) relating to ASHRAE benchmarks for energy consumption of desktop computers, where a trend towards increasing energy consumption levels from PCs was demonstrated. The work suggested updating benchmarks for peak demand between 110-200W (compared to published benchmarks of 55-75W).

The updated benchmark of 65W published in the 3rd edition of Guide F aligns well with the monitored average demand of the basic specification laptop (within 2%). However, average demand for the high specification desktop was observed to be three times higher than the updated benchmark. In this instance, the computer was used for numerically intensive computations using engineering software such as CFD. Although this would be common in engineering practices, it might be less typical in an office of administrators, for example. This highlights the importance of using appropriate benchmarks when specifying 'atypical' office equipment and a clear understanding of the intended use of a building space is needed to make reasonable estimations, which is emphasised in the new Guide F. As for the stand-by mode, both monitored computers had demands significantly lower than the benchmark published in the 2nd edition of Guide F, at approximately 10% of the benchmark values. Updated benchmarks published in the 3rd edition have been reduced significantly (from 20-30W to 6.6W) yet these are still observed to be significantly higher than monitored stand-by demand, with the highest recorder stand-by demand being less than 30% of the updated benchmark.

5.3 Computer monitors

The benchmarks for maximum, average and stand-by demands in the 2nd edition of the CIBSE Guide were observed to be significantly higher than the monitored cases. When these benchmarks were originally published in the BRECSU (1997) guide, CRT screens were the predominant technology for computer screens**.** The observed differences are likely to be because of the more recent proliferation of LCD screens, which consume much less energy. This issue has been addressed in the 3rd edition of Guide F and the updated benchmarks for average and stand-by demand provide a much better correlation with monitored loads. Focusing on average demand, measured data fluctuates by approximately 20% above and below the updated benchmark, demonstrating its suitability for a range of different LCD screens with dimensions between 19-21 inches. Updated benchmarks for stand-by power also demonstrate improved applicability, with monitored data falling almost completely within the range provided in the 3rd edition of Guide F.

5.4 Desktop Printers

Monitoring data for the single desktop printer included in this study demonstrated a significantly lower maximum demand than the benchmark published in the 2nd edition of Guide F (at 103W compared to an 800W benchmark). The monitored average consumption was observed to be significantly lower than the updated benchmark value, despite having previously fallen within the benchmark range in the 2nd edition. Meanwhile, the monitored stand-by consumption figure of 15.6W was observed to be somewhat lower than the benchmark ranges provided in both editions of Guide F (i.e. 20-30W). This highlights that the range of operation of devices can vary, although the revised benchmarks appear to be reasonable.

5.5 Photocopiers

The maximum monitored demands for photocopiers (765-772W) were observed to be approximately 50% of the benchmark published in the 2nd edition of Guide F. The average consumption of the monitored units was in the range 120-1,000W published in the 2nd edition of Guide F. In the 3rd edition of Guide F, the benchmark range for average demand by photocopiers has been increased to 550-1,100W. Monitored values now fall outside this range, being approximately 50% of the lowest margin. However, it is difficult to judge the appropriateness of the updated benchmark without taking into consideration the usage patterns of the photocopiers because electricity demand is heavily dependant on the printing/copying capacities and duties. With regards to stand-by demand, monitored loads fall within the ranges provided in both editions of Guide F, but are the lower end of the published ranges.

5.6 Vending Machines

Maximum monitored demands for the vending machines demonstrated that the benchmark value of 3000W published in the 2nd edition of Guide F was applicable mainly to units selling hot drinks. The refrigerated vending machines only reached maximum demands of 500-630W. The average consumption demands for the monitored vending machines were below the benchmark range of 350-700W. When idle, the monitored machines had significantly lower consumptions than the benchmark (300W), with the highest consuming machine having a demand of only 89W when in ‘standby’. Vending machine benchmarks have been excluded in the 3rd edition.

6 CONCLUSION

This study reviewed existing and recently updated benchmarks for small power consumption in UK office buildings. A case study building was used to obtain monitored consumption data from typical equipment and appliances providing a comparison against the old and revised benchmarks given in the 3rd edition of CIBSE Guide F.

Results from this study suggest that the benchmarks published in the 2nd edition of Guide F were broadly unrepresentative of small power equipment currently being used in office buildings. Key findings were:

- Typical desktop computers can have higher maximum demands and average energy consumption than the old benchmarks;

- Laptop computers were observed to have lower maximum demands than the old benchmarks, although average consumption values were reasonable;
- Stand-by power demand for both laptop and desktop computers were observed to be only a fraction of the old benchmarks;
- Old benchmarks for computer monitors relate to CRT monitors being unrepresentative of energy consumption by LCD monitors which are widely used in contemporary office buildings;
- Benchmarks for printers and photocopiers were fairly representative, excepting that the machine workload is not accounted for in the benchmarks, or in the study;
- Refrigerating vending machines were fairly well represented, however machines that supply heating on demand can consume significantly more energy and are heavily workload dependant, something that is not addressed in the guide.

A review of the recently published 3rd edition of CIBSE Guide F demonstrated that the updated benchmarks were generally more representative of the monitored equipment, however there were some notable observations:

- The average demand for high specification desktop computers can be significantly larger than the benchmarks suggest and hence an understanding of this equipment is critical when estimating in-use performance;
- Photocopiers required a measure of expected load if reasonable estimates are to be derived from the benchmarks;
- In all cases it would appear that the standby loads are over estimated in the new Guide, excepting that the limitations of this study may bias the results presented.

The revised Guide F is a significant step forward, offering more appropriate guidance on expected appliance consumption. However there is still work to be done to inform designers on how to better predict small power loads in-use, through the development of metrics that give an indication of typical hours of use or appliance workload. A stronger dialogue between designers and clients is also of utmost importance so that equipment specifications and operational characteristics can be accurately established, allowing designers to make better estimates on the small power energy consumption in-use.

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APPENDIX D ASSESSING THE IMPACT OF OCCUPANT BEHAVIOUR ON THE ELECTRICITY CONSUMPTION FOR LIGHTING AND SMALL POWER IN OFFICE BUILDINGS (PAPER 4)

Full Reference

Menezes, A., Tetlow, R., Beaman, C., Cripps, A., Bouchlaghem, D., Buswell, R., 2012. Assessing the impact of occupant behaviour on the electricity consumption for lighting and small power in office buildings. *7th International Conference on Innovation in Architecture, Engineering and Construction*. 15-17 August , The Brazilian British Centre, Sao Paulo, Brazil.

Abstract

Lighting and small power will typically account for more than half of the total electricity consumption in an office building. Significant variations in electricity used by different tenants suggest that occupants can have an impact on the electricity demand for these end-uses. Yet current modelling techniques fail to represent the interaction between occupant and the building environment in a realistic manner. Understanding the impact of such behaviours is crucial to improve current energy modelling techniques, aiming to minimise the significant gap between predicted and in-use performance of buildings. A better understanding of the impact of occupant behaviour on electricity consumption can also inform appropriate energy saving strategies focused on behavioural change.

This paper reports on a study aiming to assess the intent of occupants to switch off lighting and appliances when not in use in office buildings. Based on the Theory of Planned Behaviour, the assessment takes the form of a questionnaire and investigates three predictors to behaviour individually: 1) behavioural attitude; 2) subjective norms; 3) perceived behavioural control.

The paper details the development of the assessment procedure and discusses findings from the study. The questionnaire results are compared against electricity consumption data for individual zones within a multi-tenanted office building. Results demonstrate a statistically significant correlation between perceived behavioural control and energy consumption for lighting and small power

Keywords - Electricity consumption; occupant behaviour, offices, lighting, small power.

Paper type - Conference Paper

1 INTRODUCTION

Designing a building in a sustainable manner does not guarantee it will be energy efficient, as consumption is heavily influenced by the behaviour of its occupants (Derijcke and Uitzinger, 2006). This rationale carries great significance when investigating energy efficiency in buildings, and has been widely recognised in the building industry for many decades (Socolow, 1978). Post-occupancy data relating to energy use in office buildings has demonstrated significant variation in electricity consumption by different tenants occupying the same building (Menezes et al., 2011). Such variations are largely influenced by the behaviour of occupants, yet current modelling techniques fail to account for the impact of behavioural elements on energy consumption of buildings. According to Haldi and Robinson (2011), building simulation programmes are now considered relatively mature, yet their ability to characterize reality is undermined by a poor representation of factors relating to occupants' presence and their interaction with environmental controls. If we are to ultimately achieve more realistic prediction of energy consumption in buildings, occupant-related factors must be better understood and represented in predictive models.

This paper investigates the impact of occupant behaviour on the electricity consumption of an 8-storey multi-tenanted office building located in Central London, UK. The building is split into 32 zones (4 per floor) allowing for the behaviour of the occupants in each of the zones to be correlated with their sub-metered electricity consumption. This covers electricity used for lighting and small power only, as these are the end-uses occupants have direct control over. Energy used for heating, ventilation and air conditioning, as well as server rooms are not included in the study. The assessment of occupant behaviour is undertaken through a survey based on the Theory of Planned Behaviour and the methodology for developing the implemented questionnaire is explained in detail. The three precursors to behaviour are assessed individually allowing for conclusions to be drawn regarding their respective impact on energy consumption.

2 BACKGROUND

2.1 Occupant Behaviour in Buildings

Occupant behaviour plays a significant role in determining actual energy consumption in buildings, alongside physical building characteristics, local environment and systems servicing and commissioning (Steemers and Yun, 2009). According to Hoes et al. (2009), user behaviour can have a larger influence on the energy performance of a building than the thermal processes within the building facade. Numerous studies have aimed to assess the impact of occupant behaviour and activities on energy consumption through the use of simulations. Yet such an approach can be complex because of the diversity and complexity of user behaviour. In order to obtain the full effects of user behaviour it is necessary to extract corresponding useful information from real measured data (Yu et al., 2011).

Several research studies have aimed to utilise monitored energy data to quantify the impact of occupant behaviour. In 2009, Ouyang and Hokao investigated the potential for energy savings in 124 households in China by improving user behaviour. Results demonstrated that, on average, effective promotion of energy conscious behaviour could reduce energy consumption by more than 10%. More recently, Gill et al. (2010) investigated the impact of occupant behaviour on the consumption of energy and water in a low-energy housing scheme in East Anglia, UK. The key intention was to enable quantification and apportionment of building performance to occupant behaviour, aiming to explain some of the variation often detected. Results indicated that energy efficient behaviours accounted for 51%, 31% and 11% of the variance in heat, electricity and water consumption, respectively, between the 26 dwellings in the housing scheme (Gill et al. 2010).

Focusing on commercial buildings, Masoso and Grobler (2010) highlighted the impact of poor occupant behaviour on electricity consumption during non-occupied hours in office buildings. The work was based on energy audits of 6 buildings in Botswana and demonstrated that 56% of the energy consumed by the building was used outside working hours because of poor occupant behaviour whereby lights and equipment are left on at the end of the day, as well as poor zoning and controls. More recently, Haldi and Robinson (2011) developed a bespoke model following extensive field survey data allowing for occupant behaviour to be considered at design stage. This novel modelling tool accounted for occupant presence, opening and closing of windows, as well as raising and lowering of blinds. A number of other research projects (Liao and Barooh, 2010; Smarakoon and Soberato, 2011) have investigated the impact of occupancy on energy consumption, proposing novel models for predicting occupancy patterns. However, the impact of holistic occupant behaviour on energy use in non-domestic buildings is still to be investigated in depth.

2.2 Theory of Planned Behaviour

Gill et al. (2010) successfully implemented a novel methodology for quantifying the impact of occupant behaviour on the energy performance of residential buildings based on the Theory of Planned Behaviour (TPB). Originally developed by Ajzen (1991), the TPB is one of the most widely applied behavioural models (Armitage and Conner, 2001). It proposes that human action is guided by behavioural attitude, subjective norms and perceived behavioural control, and can be predicted provided that the behaviour is intentional (Francis et al., 2004). In essence, TPB claims that, in order to predict whether a person intends to do something, it necessary to know (Azjen, 1991):

- Whether the person is in favour of doing it (‘behavioural attitude’)
- How much the person feels the social pressure to do it (‘subjective norm’)
- Whether the person feels in control of the action in question (‘perceived behavioural control’)

By adjusting these three ‘predictors’, the likelihood that the person will intend to carry out a desired action can be increased, thus increasing the chance of the person actually doing it. This concept is illustrated in Figure 1.

As shown, the three predictors are jointly responsible for shaping an individual's intention to perform a given behaviour. The TPB also suggests a direct link between perceived behavioural control and the achievement of a specific behaviour. This should not be confused with *actual* control (i.e. the availability of vital opportunities and resources such as time, money, skills, etc). Although the importance of *actual* control is indisputable, perceived behaviour control is of greater psychological interest, following the premise that people's behaviour is strongly influenced by their confidence in their ability to perform it (Azjen, 1991). Actual control is, strictly, irrelevant since if an individual does not also feel in control of an action they will not form an intention to do so. According to the TPB, perceived behaviour control can often be used as a substitute for a measure of actual control, providing a direct link to behavioural achievement.

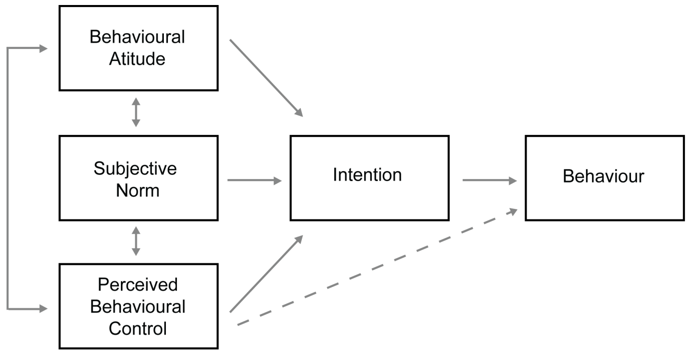


Figure 1: Theory of Planned Behaviour (adapted from Ajzen, 1991)

It is worth noting that intentions are precursors to behaviours and although there is no perfect relationship between behavioural intention and actual behaviour, TPB relies on the assumption that intention can be used as a proximal measure of behaviour (Francis et al., 2004). This observation was one of the most important contributors of the TPB model when compared to previous models of attitude-behaviour relationship, allowing for the variables in this model to be used to determine the effectiveness of interventions even if there is no readily available measure of actual behaviour. This is both a strength and a limitation of the TPB, being a source of criticism by Martiskainen (2007) who suggests that the model is more applicable to measuring the relationships between behavioural constructs than the measurement of actual behaviour. However, a review of the TPB (Armitage and Conner, 2001) concluded that the TPB accounts for a considerable proportion of variance in actual behaviour, supporting the TPB as a predictive theory of intention and behaviours.

3 METHODOLOGY

This study was undertaken in an 8-storey multi-tenanted office building located in Central London, consisting mainly of open-plan office spaces. Each floor has a treated floor area of approximately 2,000m^2, and is divided into 4 sectors, providing 32 individual zones that can be let to different tenants. In order to assess the impact of occupant behaviour on electricity consumption, each of the 32 zones were regarded as individual data collection points. Two distinctive sets of data were acquired for each of the zones: one pertaining to the use of electricity for lighting and small power, and the other regarding the occupant behaviour, as described below.

3.1 Electricity Consumption Data

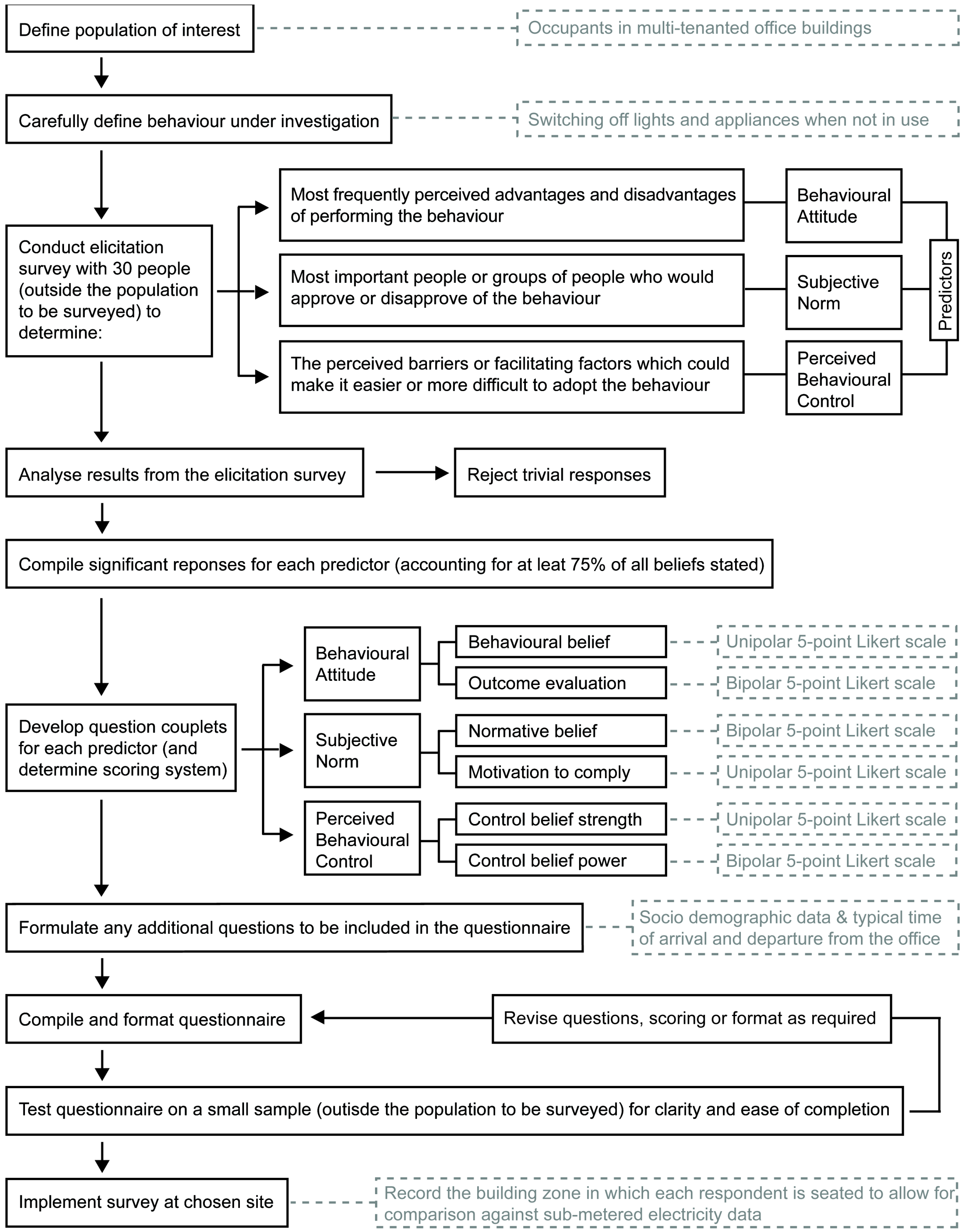
Electricity consumption data was acquired through the existing metering configuration of the building. This consists of two incoming meters: one for the landlord supply and one for the tenants supply. The landlord consumption includes all HVAC equipment and controls, as well as lighting throughout the common areas of the building, with no further sub-metering. Meanwhile, tenant consumption includes all the electricity supplied for lighting, small power equipment and server rooms throughout the building. A total of 36 sub-meters provide a further breakdown of the tenant electricity supply: one for each of the 32 zones in the building plus 4 separately metered server rooms (not considered in this study). Monthly electricity consumption data was recorded for each of the 32 sub-metered zones, yet only 27 of them were deemed appropriate for inclusion in the study. This was because 2 zones were unoccupied and 3 zones were reception areas consisting mainly of transitional spaces.

3.2 Assessing Occupant Behaviour

Francis et al. (2004) provides a thorough framework for survey development using the TPB. The methodology characterises each contributing behavioural construct (behavioural attitudes, subjective norms and perceived behavioural control) and was used to develop the questionnaire used in this study. Figure 2 illustrates this methodology, highlighting key actions taken during the development and implementation of the questionnaire.

The first step was to define the population of interest, this being: *occupants in a multi-tenanted office building*. Defining the exact behaviour under investigation was not quite as straight forward, because occupants are able to affect electricity consumption in multiple and diverse ways. Considering the focus of the study involved electricity use only for lighting and small power, the key behaviour for investigation was defined as: *switching off lighting and appliances when not in use*. This behaviour was deemed appropriately representative of the key interactions between occupant and energy consuming devices in the workplace.

Prior to the development of the questionnaire, an elicitation survey was conducted with 30 people outside of the population to be surveyed (i.e. not working in the building under investigation). This consisted of six open-ended questions relating to each of the three predictors to establish the dominant factors that contribute to decisions regarding the target behaviour (as described in Figure 2). Respondents were asked to provide three responses to each question and caution was taken to ensure a wide range of backgrounds and age groups were included. The results for the survey were analysed and trivial responses were rejected, ensuring that at least 75% of all beliefs were accounted for. These were then used to develop a multiple choice questionnaire whereby each significant belief was transformed into a question couplet, in line with guidance from Francis et al. (2004). Once again, this process is illustrated in Figure 2, resulting in a questionnaire with six groups of six questions (i.e. two sections for each predictor of behaviour, with every question having an equivalent couplet).



Note: Information within dashed boxes relate to choices / actions specific to this study.

Figure 2: Methodology flow chart for developing survey based on the TBP

Scoring scales were established for each group of questions using a 5-point Likert scale as standard. The direction of the scale (i.e. bipolar or unipolar) was determined to suit each set of question groups appropriately, ensuring that each predictor had a unipolar and bipolar group of questions. This is to ensure consistency in the scoring for each predictor, as follows:

- Behavioural attitude score: $\sum_{i=1}^{i=6}(\text{behavioural belief}_i \times \text{outcome evalation}_i)$
- Subjective norm score: $\sum_{i=1}^{i=6}(\text{normative belief}_i \times \text{motivation to comply}_i)$
- Perceived behavioural control score: $\sum_{i=1}^{i=6}(\text{control strength}_i \times \text{control power}_i)$

The questionnaire was complied and piloted on five people (outside the population to be surveyed) to ensure clarity and ease of completion. Minor revisions were made in line with the feedback received. Additional questions were also added to capture social demographic data as well as typical time of arrival and departure from the office.

3.3 Implementation of Survey

The questionnaires were distributed to all occupants in the building (approximately 800 people) between 08:00 and 10:00 hours on 1st November 2011. Respondents were informed that the questionnaires would be collected after 3pm on the same day. Care was taken to annotate each questionnaire with the zone in which the respondent was seated. This was crucial to allow for comparison against the electricity consumption data for each building zone. A total of 432 completed questionnaires were collected, representing a response rate of approximately 50%. Scores for each of the three predictors were calculated for each respondent and the median score for each predictor was determined for all 27 building zones included in the study.

4 RESULTS

Figure 3 illustrates the correlation between monitored monthly electricity consumption and the median scores of the occupants of each zone on each of the three predictors of the Theory of Planned Behaviour. Each individual has limited control over the electricity consumption within his or her zone, relative to the influence they may have on the average TPB predictor scores for their zone (particularly in more sparsely occupied zones). Therefore median values were used to represent the behavioural scores in each of the 27 zones in order to reduce the possibility of results being distorted by individuals with extreme scores for one or more of these measures.

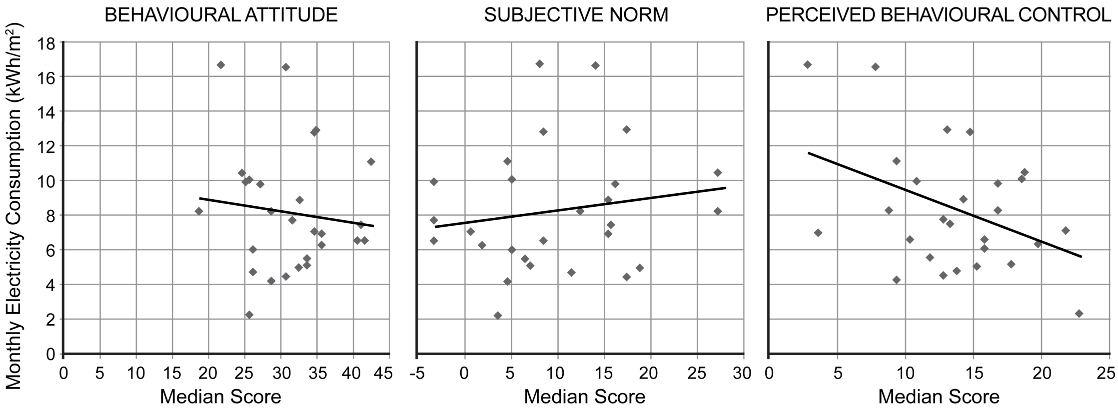


Figure 3: Scatter plots of electricity consumption vs. median scores

A multiple regression analysis was conducted to predict the monthly electricity consumption based upon the three components of the TPB. The predictors were entered into the regression analysis in the order: behavioural attitude, perceived behavioural control and subjective norms. This revealed that behavioural attitude alone did not account for a significant proportion of the variation in electricity consumption across the building, with $R^2 = 0.013$, $F(1, 25) = 0.330$, $p = 0.571$, where the *F*-statistic will tend to be smaller when the predictor does not account for variation in electricity consumption. Meanwhile, p indicates the calculated probability of observing these results, by chance alone, given no effect of the predictor on electricity consumption. By convention, $p < 0.05$ represents a statistically significant result. As seen, there is no statistically significant correlation between behavioural attitude scores and monthly electricity consumption. However, when perceived behavioural control was added to the model, this accounted for a significant proportion of the monthly electricity variance, with R^2 change = 0.168, $F(1, 24)= 4.94$, $p = 0.036$. Finally, when subjective norms were added as a predictor, these did not significantly add to the predictive value, with R^2 change = 0.01, $F(1, 23)= 0.289$, $p = 0.596$.

It is important to note that any variation that could be predicted either by perceived behavioural control or by subjective norms would, in this analysis, be ascribed solely credited to perceived behavioural control because this predictor was entered into the analysis first. Hence, to ensure that the already established effects of perceived behavioural control were not masking the effects of subjective norms, a second regression analyses was undertaken reversing the order in which the predictors were entered into the model. Results demonstrated that subjective norms alone did not account for a significant proportion of the variation in monthly electricity consumption, with $R^2 = 0.029$, $F(1, 25) = 0.743$, $p = 0.397$. However, when perceived behavioural control is added as a predictor, approximately 16% of the variation in monthly electricity consumption is now accounted for, with R^2 change = 0.156, $F(1, 24) = 4.61$, $p = 0.042$. Finally, as expected, adding behavioural attitude scores as the last predictor did not account for significantly more variation in electricity consumption than subjective norms and perceived behavioural control combined, with R^2 change = 0.006, $F(1, 23) = 0.181$, $p = 0.675$.

Based on the results from the multiple regression analysis, perceived behavioural control is the only predictor that has a statistically significant impact on electricity consumption. Using a linear regression analysis with perceived behavioural control as the sole predictor of monthly electricity consumption, it accounts for approximately 17% of the variation in monthly electricity consumption, with $R^2 = 0.169$, $F(1, 25) = 5.09$, $p = 0.033$.

5 DISCUSSION

Results from this study have demonstrated that, of the three predictors in the Theory of Planned behaviour, perceived behavioural control is the only one with a significant correlation to monitored electricity consumption. In the building under investigation, this implies that lower energy consumption can be expected in zones where occupants perceive themselves to have a high level of control over lighting and appliances. No correlation was found between either behavioural attitude or subjective norms, and monitored electricity consumption for the zones.

The structure of the TPB goes some way towards explaining these findings. As previously discussed, the TPB proposes a direct link between perceived behavioural control and behaviour, whereas the other predictors are linked only to intention. In this particular study, results suggest that perceived behavioural control could be used as a substitute for a measure of actual control, providing a direct link to behavioural achievement. This is understandable, as it is likely that occupants in the same zone would have a similar ability to adjust the physical controls that turn lighting and appliances off. While the scores for behavioural attitude and subjective norm would vary greatly between different individuals, the scores for perceived behavioural control would not vary as much, as this is heavily linked to actual measures of control.

Traditional attempts to reduce the influence of occupants on energy consumption revolve around the assumption that people's behaviour can be altered by providing them with information about their undesirable actions. However, there is evidence to suggest that while this approach may serve to influence attitudes, it often has a negligible effect on actual behaviour (McKenzie-Mohr, 2000). The results of this study support these findings by suggesting that the attitudes and subjective norms of the occupants have little discernable influence on their zone's electricity consumption. Instead it is their perceived level of control over lighting and small power that has a significant impact on their electricity use. This finding highlights the importance of considering how building users can control their environmental conditions during the design process, arguing against efforts to reduce the level of control users have over appliances and lighting. This would suggest a clear benefit in implementing usable and well located controls rather than technologies such as PIR (passive infra-red) detection and other automated services.

It is important to emphasise that TPB only considers planned behaviour, so for the purposes of this study it can only be used to explain the variation in electricity consumption caused by the conscious operation of lighting and appliances. The intangible nature of electricity use renders it likely that a certain proportion of electricity consumption in buildings is a result of unplanned or instinctive behaviour which will not be accounted for by TPB.

Following the completion of the survey some occupants highlighted that, in a number of questions, they might have given two different answers if lighting and small power had been dealt with individually. A subsequent survey will be undertaken to separately account for variations in behaviour for both end-uses individually. This will be carried out in a building where lighting and small power are sub-metered separately, allowing for a more detailed analysis of the impact of occupant behaviour on electricity consumption for each end-use.

6 CONCLUSION

This study has investigated the impact of occupant behaviour on the electricity consumption for lighting and small power in a multi-tenanted office building in London, UK. The methodology used to undertake this assessment was based on the Theory of Planned Behaviour, dealing with each predictor to behaviour individually. Results demonstrated a statistically significant negative association between scores for perceived behavioural control and electricity consumption, suggesting that perceived lack of behavioural control can account for variations of up to 17% in electricity consumption in each of the building zones. The impact of behavioural attitude and subjective norms on electricity use were non-significant and may be deemed negligible in the specific building under investigation.

Findings from the study suggest that the more control people perceive to have over their surroundings, the less energy they consume. This premise goes against the current design trend for more automated buildings and will be investigated in further detail in a subsequent study to be carried out in a different multi-tenanted building. It is envisioned that further findings will be used to inform better predictions of energy consumption in office buildings allowing for occupant behaviour to be more adequately accounted for. Occupant behaviour is significantly more complex than is allowed for in current energy modelling techniques and this must be tackled if realistic predictions of energy performance are to be achieved.

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APPENDIX E ESTIMATING THE ENERGY CONSUMPTION AND POWER DEMAND OF SMALL POWER EQUIPMENT IN OFFICE BUILDINGS (PAPER 5)

Full Reference

Menezes, A., Buswell, R. A., Cripps, A., Bouchlaghem, D. and Wright, J., 2013. Estimating the energy consumption and power demand of small power equipment in office buildings.

(Manuscript submitted to Energy and Building Journal on 8th July, 2013).

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 them, relying on an increasing use 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. With the fast paced changes to the workplace, there is scope to investigate the use of small power equipment in office buildings to inform better prediction of small power energy use. 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 to estimate small power consumption, 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.

Keywords - Small power, plug loads, offices, predictions, estimates, computers, energy consumption, power demand, operational performance

Paper type - Journal Paper (under review)

1 INTRODUCTION

As buildings become more energy efficient, small power equipment such as computers are becoming increasingly significant as an energy end-use (Kaneda et al., 2010). A study published by the New Buildings Institute suggest that plugs loads can represent up to 50% of the electricity use in a building with high efficiency lighting, heating and cooling (NBI, 2012). 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 (Jenkins, et al., 2008).

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 ratings will significantly overestimate the casual gains resulting in the specification of chillers with a higher capacity than needed (Komor, 1997). This can result in increased capital cost as well as higher operating costs through greater part load operation (Dunn & Knight, 2005). Designers often rely on published benchmarks in order to account for small power demand in office buildings (BCO, 2009) yet these are sparse and often out of date (Menezes et al., 2013).

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 (Menezes et al., 2013; Carbon Trust, 2006). 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, depicted in Table 1 (BRECSU, 2000). 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 the building is conditioned. From a small power perspective however, such classifications aren’t 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

Table 1: ECG19 benchmarks for small power consumption (i.e. office and catering equipment)

	Electricity Consumption (kWh/m^2)		Power Load Density (W/m^2)	
	Good Practice	**Typical**	**Good Practice**	**Typical**
Type 1: Naturally ventilated cellular	14	21	10	12
Type 2: Naturally ventilated open plan	23	32	12	14
Type 3: Air conditioned standard	28	37	14	16
Type 4: Air conditioned prestige	36	47	15	18

ECG19 also provides benchmarks for power load density, varying from 10 to 18 W/m^2. 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 figure of 15W/m^2 can be used to represent typical small power load in general offices (BSRIA, 2011). 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/m^2 (BCO, 2009). The recently updated CIBSE Guide F (CIBSE, 2012) suggests that a benchmark figure for building loads of 25 W/m^2 is adequate for most office buildings (with 15 W/m^2 when diversity is taken into account) . 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. Aiming to address such variations CIBSE Guide F provides an alternative methodology for calculating installed loads based on a 'bottom-up' approach (CIBSE, 2012). This method was adapted from Energy Consumption Guide 35, and enables a more robust prediction of power demand and energy consumption (BRECSU, 1993). 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 usage patterns of individual desks/workstations, accounting for communal appliances separately (CIBSE, 2013).

Computers are commonly the single biggest source of energy use, also contributing significantly to internal heat gains (Menezes et al., 2013; Carbon Trust, 2006). Moorefield et al. (2011) conducted a monitoring study of small power use in 25 offices in California over a 2-week period. Power demand data for 470 plug load devices was collected at 1-minute intervals through the use of plug monitors and the data were extrapolated based on an inventory of nearly 7,000 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 (Bray, 2006). 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 (EPA, 2012). Published data suggests that newer computers require less energy in 'low power' modes than older computers (Roberson et al., 2002; Kawamoto et al., 2001), however, the demand for computers with increased processing power has resulted in higher power demands when the computers are active, as illustrated in Figure 1 (adapted from Roberson et al., 2002; Kawamoto et al., 2001).

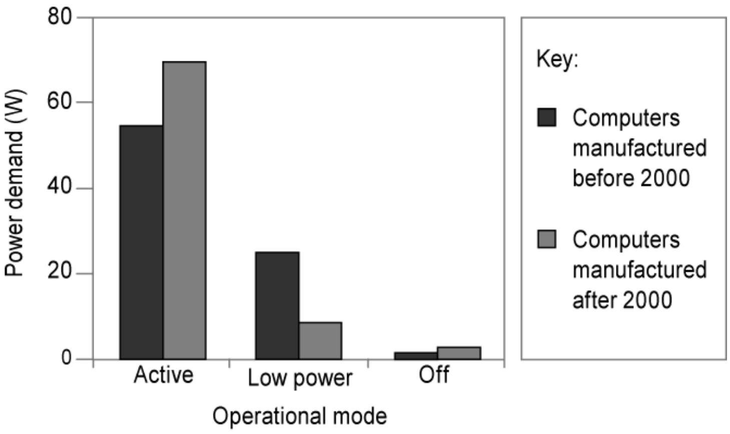

Figure1: Energy requirements of desktop computers manufactured before and after 2000

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 (Menezes et al., 2013). 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 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 (Bray, 2006). 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 overall energy consumption of office buildings: laptop shipment figures are projected to be triple that of desktops in the next few years (Meeker et al., 2010). 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 (BECTA, 2006). This technology reduces power demand and resultant heats gains locally by shifting these to centralised processors with higher efficiencies (DEFRA, 2011).

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

Source	Power Demand (W)					
	Desktop computers			Laptop Computers		
	Active	Low Power	Off	Active	Low Power	Off
Wilkins & McGaffin (1994)	56	56	-	-	-	-
Nordman et al. (1996)	36-55	32-49	0-2	-	-	-
Mungwititkul & Mohanty (1997)	36-48	27	-	-	-	-
Kawamoto et al. (2001)	30-60	25	1-3	12-22	1.5-6	1.5-2
Roberson et al. (2002)	70	9	3	19	3	-
Hosni and Beck (2010)	50-100	-	-	15-40	-	-
Moorefield et al. (2011)	79	3.2	-	74.7	1.6	-
Menezes et al. (2013)	64-169	-	1.9-2	18-41	-	0.3-1

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 (Bray, 2006). 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 and Grobler (2010) 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. 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% (Webber et al., 2006). 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 hours a day, being in active mode for 3 hours per day (Kawamoto et al., 2004).

Studies dating back to the 90's suggest that on average, computers are active for approximately 9% of the year (Mungwititkul and Mohanty, 1997). In a detailed monitoring study of 3 desktop computers, Nordman et al. (1996) calculated that computers were active between 17-31% of the time during workdays, falling to 9-16% when all days were considered . More recently, Moorefield et al. (2011) monitored 61 desktops and 20 laptop computers in-use in 25 offices in California over a two-week period. 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 (NBI, 2012). 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 minutes of inactivity, 76% of the idle time would be spent on low power mode (Kawamoto et al., 2005). Alternatively, setting the time delay to 60 minutes 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, 2003) demonstrated that aggressive power management (powering down computers after 5 minutes of inactivity) resulted in a reduction of annual energy consumption by approximately 75% compared to a scenario when no power management settings were applied.

When estimating the peak demand and energy consumption of computers, it is also vital to consider usage diversity (Parsloe and Hebab, 1992). 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 (Wilkins and Hosni, 2000). Diversity factors need to be applied to load calculations in order to limit oversizing of cooling plant (Komor, 1997). 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 (Moorefield, 2011). 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 to 78% (Mungwititkul and Mohanty, 1997). More recently, Wilkins and Hosni (2011) 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. Measured diversity during weekends were 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 (Myerson and Ross, 2006). 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 (Fleming, 2011). 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 development of workplaces also suggest that further reliance on ICT is likely to occur regardless of the adoption of flexible working practices (Worthington, 2005).

A recent study modelled the impact of two possible future scenarios for computer use in office buildings (Johnston et al., 2011):

- Energy conscious scenario: ICT acquisition policy is driven by an effort to minimise energy consumption and carbon emissions
- 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

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-minute 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-minute sample rates and equipment with similar specifications were 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 Lanzisera et al. (2013) sampling faster than at 1-minute intervals does not provide significant benefit and that monitoring periods longer than a few months provides little improvement in estimating annual energy use. 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.

Table 3: Equipment in the database and installed quantities in the office space under investigation

Equipment type	Database			Quantity of installed equipment	Percentage of installed equipment monitored
	Quantity of monitored equipment	Weekday profiles	Weekend profiles		
Laptop computer	8	512	240	99	8.1%
High-end desktop computer	3	180	78	19	15.8%
Low-end desktop computer	2	120	52	22	9.1%
19” LCD screen	2	120	52	128	1.4%
21” LCD screen	1	60	26	22	4.5%
Large photocopier	1	60	26	4	25%
Plotter	1	60	26	1	100%
Coffee machine	2	40	16	2	100%
Fridge	1	20	8	2	50%

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 as follows:

$$u = t.S\sqrt{1 + \frac{1}{n}}$$

Where: u is the uncertainty, t is the 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.

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_{off} is the lowest power draw whilst the equipment is connected to the mains.
- P_{low} is defined as a low power mode that the computer is capable of entering automatically after a period of inactive.
- P_{on} represents the average power demand for all the difference operational modes whilst the machine is active.

According to Wilkins and Hosni (2011), two modes of operation (active and low) are appropriate for the purpose of load calculations. 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 proportion of time on idle whilst operational (EPA, 2012). 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 (Energy Star, 2013). 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 'Efergy energy monitoring socket' (with accuracy within 2%) are widely available and can provide live readings of power demand (Efergy, 2013).

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 the 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 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 4 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.

Table 4: Equipment inputs for Model 2

Equipment type	Quantities		Power Draw (W)			Usage Profiles (% time)			
	Absolute	(%)	Off	Low active	On (average)	Transient	Strict Hours	Extended Hours	Always On
Computers									
High-end desktops	19	(14%)	1	80	150	15%	30%	30%	25%
Low-end desktops	22	(16%)	1	30	40	10%	70%	10%	10%
Laptops	99	(71%)	1	20	30	30%	30%	40%	0%
Screens									
19" LCD screen	128	(85%)	0	1	25	20%	50%	30%	0%
21" LCD screen	22	(15%)	0	1	45	20%	50%	30%	0%
Printers & copiers									
Photocopier	4	(80%)	30	30	220	0%	0%	100%	0%
Plotter	1	(20%)	120	120	170	0%	0%	100%	0%
Catering									
Fridge	2	(50%)	0	100	120	0%	0%	0%	100%
Coffee Machine	2	(50%)	25	25	350	0%	0%	0%	100%

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). A prompt also enquires whether reduced occupancy is expected during lunchtime and if so, when this is likely to occur. Table 5 illustrates the operational and benchmarking inputs used to characterise the office space under investigation.

Table 5: Operational inputs for Model 2

Usage diversity (weekday)	75%
Usage diversity (weekend)	15%
Tarr (norm)	09:00
Tdep (norm)	17:00
Tarr (ext)	08:00
Tdep (ext)	19:00
% of computers switched off at the end of the day	60%
Reduced occupancy at lunchtime?	yes
Start time	12:00
End time	13:00

Wilkins and Hosni (2011) suggest that a diversity factor of 75% should be applied to computers in load calculations, with weekend usage diversity ranging from 10% to 30%. 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 (2011) demonstrate that peak diversity can vary on a daily basis, ranging by up to 20%. 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 (2011).

Usage Profiles

The operational inputs are used to adjust the usage profiles as illustrated in Figure 2 and Figure 3. P_{base} represents the base-load and is calculated based on the proportion of equipment switched off, representing a ratio between P_{off} and P_{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_{lunch} is estimated to be = P_{on} x 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.

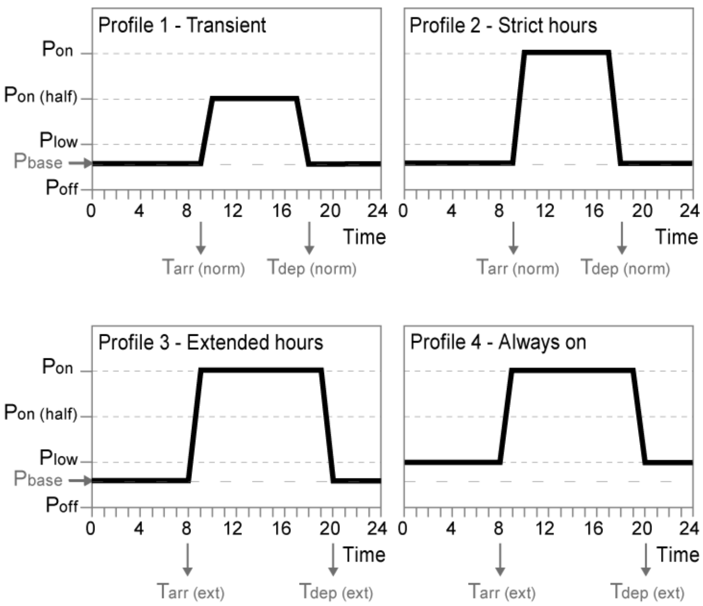

Figure 2: Usage profiles applied to computers in Model 2

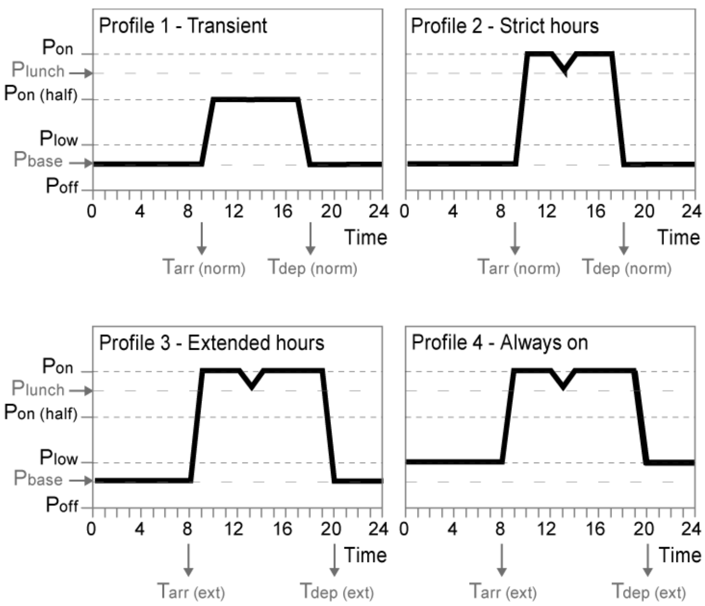

Figure 3: Usage profiles applied to computer screens in Model 2

Outputs

The model calculates power demand profiles in kW (and W/m^2) 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.

Figure 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).

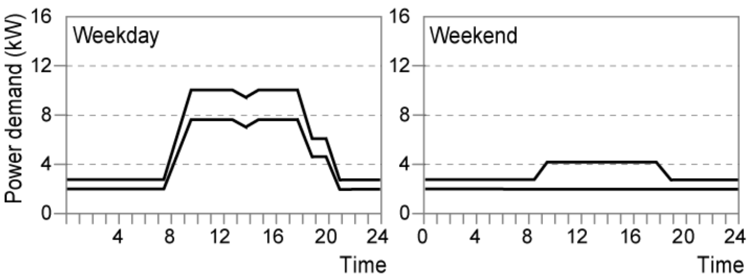

Figure 4: Weekday and weekend profiles generated by Model 2

4 RESULTS

4.1 Model 1: Comparison against metered data

Figure 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-minute intervals, metered data is illustrated in 15-minute intervals, as that is the highest resolution available with the AMR system. The metered profiles fall within the predicted range before 8am and after 8pm (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 (1-minute vs. 15-minute intervals) 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-minute 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.

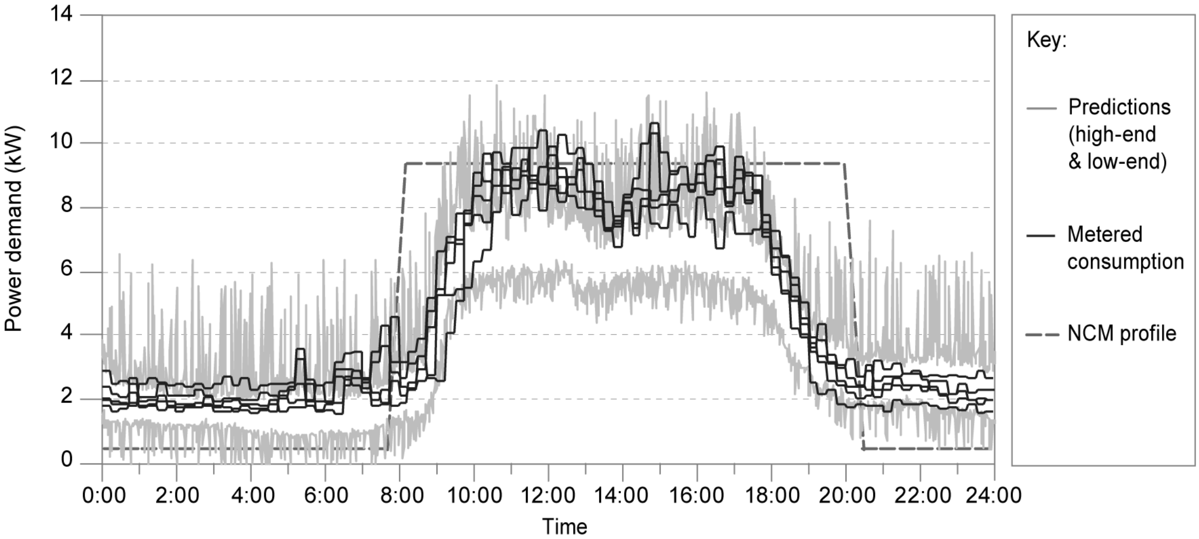

Figure 5: Predictions and metered weekday power demand profiles using Model 1

Figure 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).

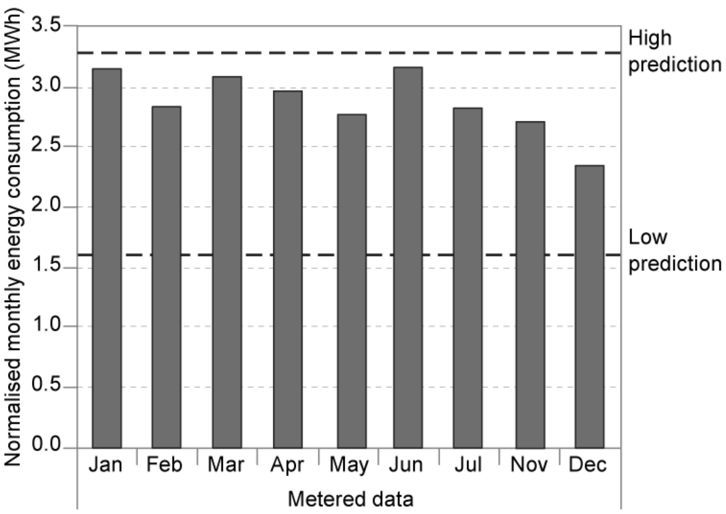

Figure 6: Predictions and metered monthly energy consumption using Model 1

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 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

Figure 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 falls 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-hour intervals whereas the metered data has a frequency of 15 minutes. This discrepancy in granularity between both sets of data inherently presents a challenge to the prediction tool, yet results are still reasonable.

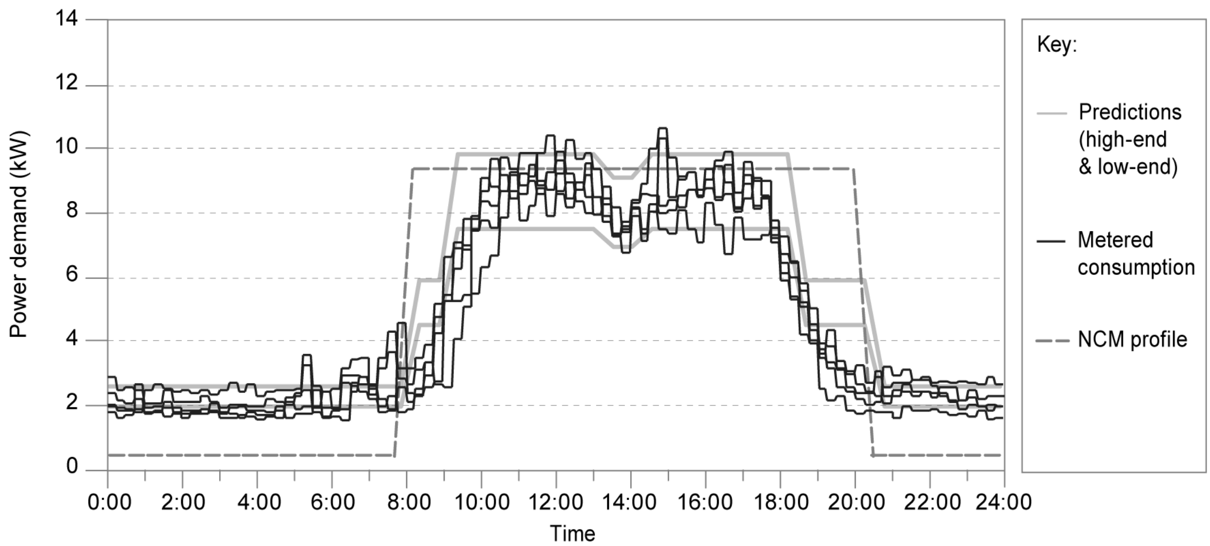

Figure 7: Predictions and metered weekday power demand profiles using Model 2

Figure 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.

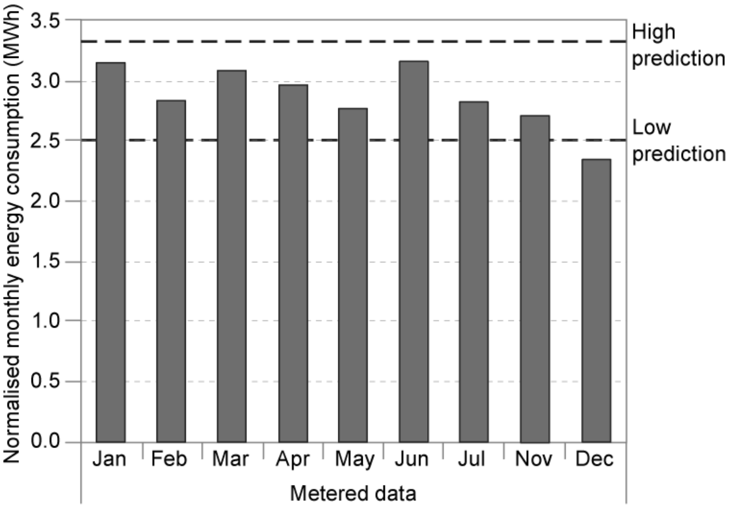

Figure 8: Predictions and metered monthly energy consumption using Model 2

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 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 area under investigation. Some of the equipment installed in the office used for the validation were 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 7am to 7pm daily. As such, a stable load of 3 kW was added to the calculated profile between 7am and 7pm. Considering the more unstable 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.

Figure 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. 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 heat gains.

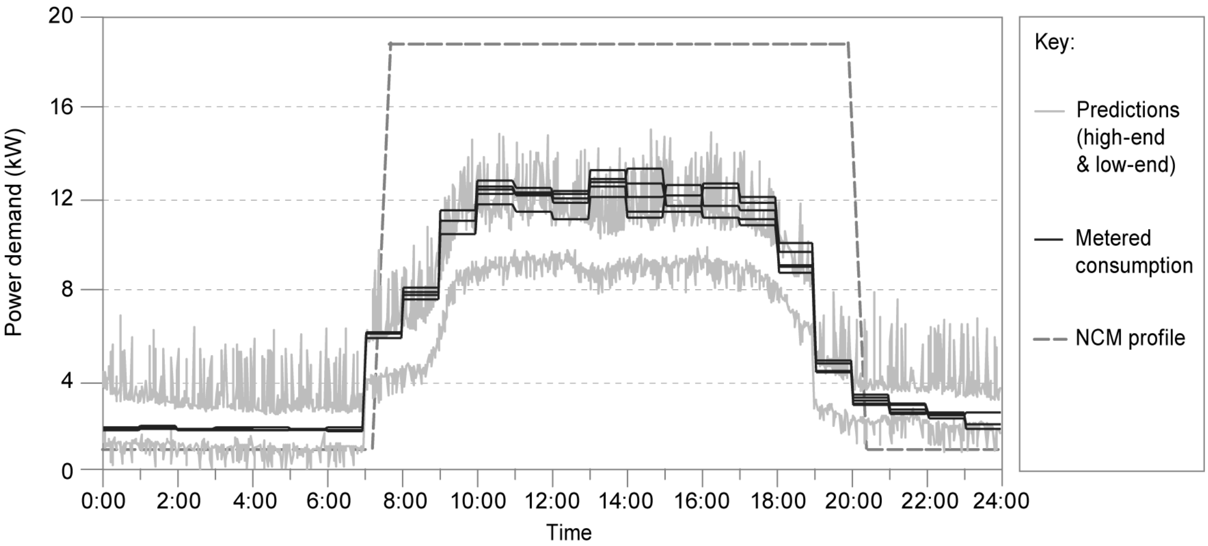

Figure 9: Predictions and metered weekday power demand profiles for the validation of Model 1

Figure 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.

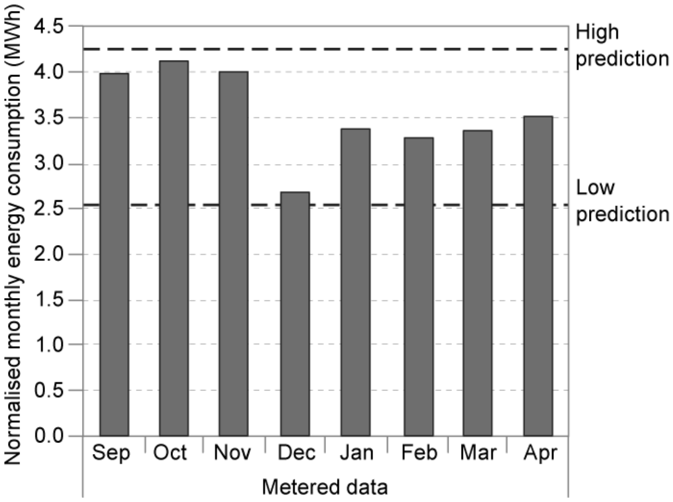

Figure 10: Predictions and metered monthly energy consumption for the validation of Model 1

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).

Figure 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 8pm).

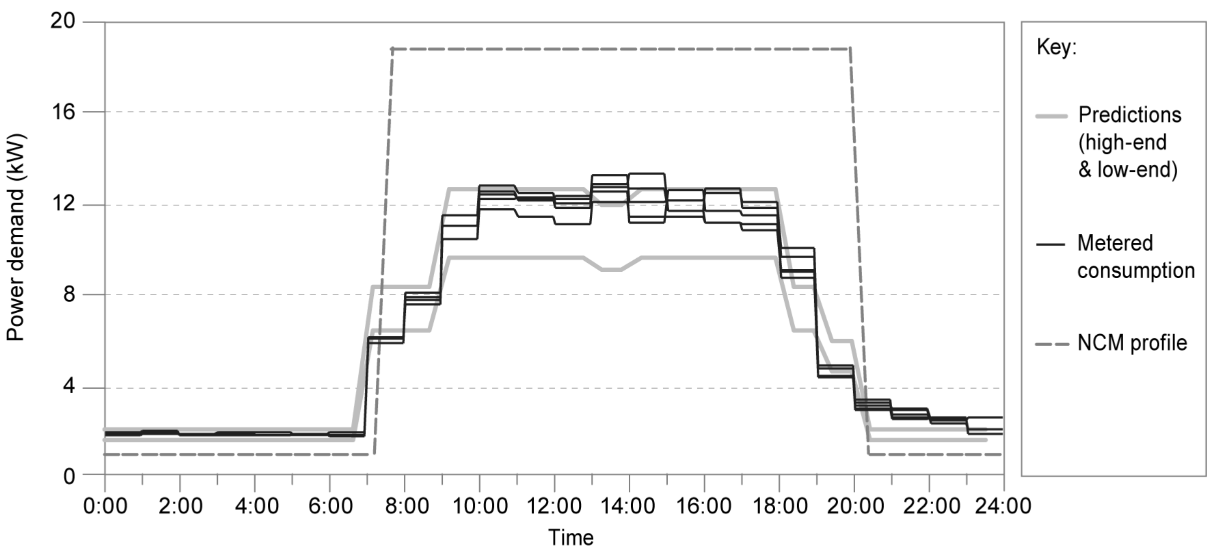

Figure 11: Predictions and metered weekday power demand profiles for the validation of Model 2

Figure 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').

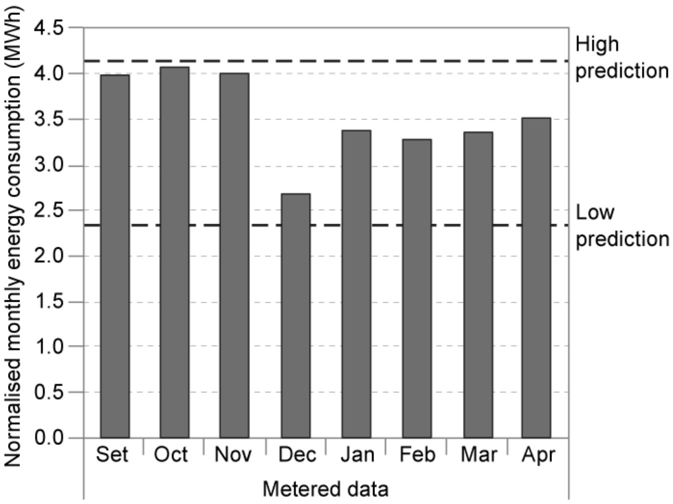

Figure 12: Predictions and metered monthly energy consumption for the validation of Model 2

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 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-hour intervals) were still observed to be representative of metered data in intervals as small as 15-minutes. 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.

Figure 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). 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. For contextual reference, a wider range including benchmarks for all office types included in ECG19 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 ECG19 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.

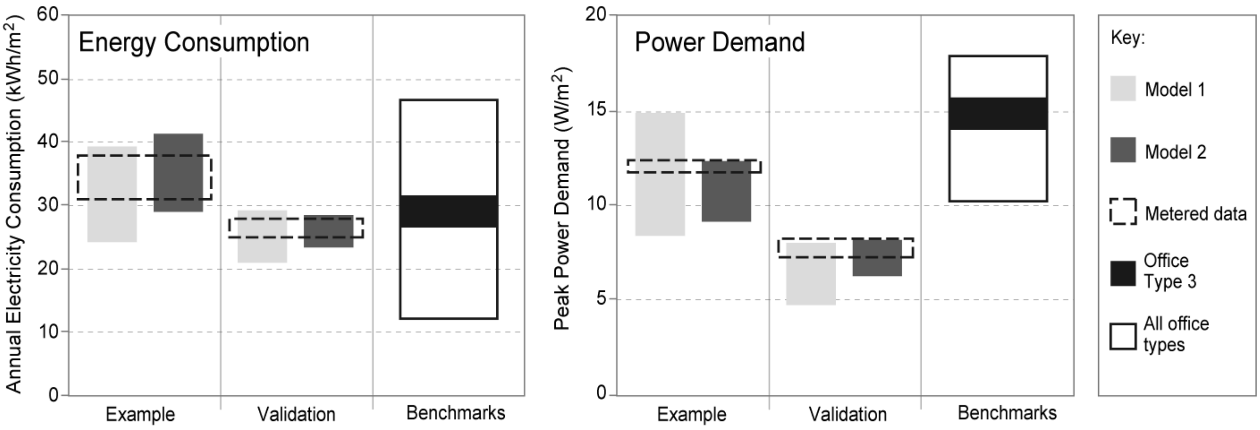

Figure 13: Comparison of model results against ECG19 benchmarks

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 CONCLUSION

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 patters 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 ECG19 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.

8 REFERENCES

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APPENDIX F OCCUPANT BEHAVIOUR QUESTIONNAIRE DEVELOPMENT

The occupant behaviour questionnaire utilised in this research project was developed in line with guidance by Francis et al. (2004). This widely referenced document provides a thorough framework for survey development based on the Theory of Planned Behaviour (TPB) and is aimed at researchers in the health sector. The guidance is however applicable to research in the field of built environment as the underlying theory is consistent no matter the setting.

Francis et al. (2004) proposes three methods for measuring behavioural intention: (i) intention performance; (ii) generalised intention; and (iii) intention simulation. Francis et al. (2004) suggests that the 'generalised intention' method be used unless either of the other methods would present particular benefit to the study. This was not deemed to be the case so method 2: 'generalised intention' was implemented. The guidance also provides two alternatives for measuring attitudes, subjective norms and perceived behavioural control: (i) direct and (ii) indirect. The indirect approach was undertaken based on precedent set by Gill et al. (2010). The indirect method also provides a more robust framework for questionnaire development.

The first two steps in developing a questionnaire were to define the population of interest and the behaviour under investigation. The population of interest was defined as: occupants in a multi-tenanted office building. The behaviour under investigation was defined as: 'switching off lighting and appliances when not in use'. The next step was to undertake an elicitation study with 30 people outside the population to be surveyed (i.e. not working in the building under investigation) but still within the population of interest (i.e. office workers). This consisted of six open-ended questions relating to each of the three predictors to establish the dominant factors that contribute to decisions regarding the target behaviour, as detailed in Table 1 below.

Table 1: Questions included in the elicitation survey

Q1.	What do you believe are the ***advantages*** of switching off appliances and lighting when they are not in use at your workplace?
Q2.	What do you believe are the ***disadvantages*** of switching off appliances and lighting when they are not in use at your workplace?
Q3.	Do you feel that there are any individuals or groups who would ***approve*** of you switching off appliances and lighting when they are not in use at your workplace?
Q4.	Do you feel that there are any individuals or groups who would ***disapprove*** of you switching off appliances and lighting when they are not in use at your workplace?
Q5.	What factors or circumstances do you feel make it ***easy*** for you to switch off appliances and lighting when they are not in use at your workplace?
Q6.	What factors or circumstances do you think make it ***difficult*** or impossible for you to switch off appliances and lighting when they are not in use at your workplace?

Respondents were asked to reflect on their own experiences and to be as honest as possible, providing up to 3 responses per question. Additional information regarding the aims and scope of the study were also provided, alongside a description of which specific appliances and lighting fixtures should be considered. Care was taken to ensure a wide range of backgrounds (e.g. work sectors, job titles, etc) and age groups were included in the study.

Table 2: Summary of responses for the elicitation survey

	Respondent no.																														Total no. of responses	Cumulative % of total responses
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30		
ATTITUDE: What do you believe are the ***advantages*** of switching off appliances and lighting when they are not in use at your workplace?																																
Save money (lower bills)	1	1	1		1		1	1	1	1	1	1	1	1	1	1			1	1	1	1	1		1	1	1	1		1	24	18%
Save energy	1	1		1	1	1		1	1	1	1	1		1	1		1	1	1		1	1	1	1	1	1			1	1	23	35%
Slow start up time	1	1	1	1	1		1		1	1	1	1		1	1			1	1		1		1		1	1	1	1		1	21	51%
Reduce CO_2 emission	1	1	1	1	1		1	1					1	1		1			1	1		1						1			14	61%
Increased lifespan of appliances			1	1						1			1		1			1						1	1		1		1		10	69%
Inconvenience			1					1	1				1	1	1								1			1				1	9	**75%**
Security implications (lights only)		1		1						1						1															4	78%
Remote login (computers only)					1												1		1										1		4	81%
Loss of data													1			1				1					1						4	84%
Less internal gains				1														1								1					3	87%
Eye strain (low lighting levels)							1					1								1											3	89%
Appliances work better				1						1																					2	90%
H&S - less risk of short circuit																	1							1							2	92%
Increase heating loads	1																	1													2	93%
Energy usage at start-up of appliances																		1											1		2	95%
May affect many people - reluctance																							1								1	96%
Software updates (computers only)										1																					1	96%
Reduced noise in the workplace																										1					1	97%
Set an example												1																			1	98%
Difficulty in switching lights back on	1																														1	99%
Higher wear and tear of appliances													1																		1	99%
Not interupting processes																	1														1	100%
SOCIAL NORM: Do you feel that there are any individual or groups who would ***approve*** of you switching off appliances and lighting when not in use at your workplace?																																
Line manager / boss / company partners	1										1	1	1	1	1		1			1	1	1	1		1	1	1	1	1		16	24%
Facilties manager	1	1							1			1	1			1			1				1						1		9	37%
Environmentally concious colleagues		1		1		1		1	1										1			1	1				1			1	10	52%
Finance manager								1										1		1		1	1		1	1	1				8	64%
People who work late/early (long hours)	1	1				1			1						1		1														6	73%
People who want to get their work done															1				1		1					1					4	**79%**
IT support team													1						1						1						3	84%
Energy efficiency agencies																									1			1		1	3	88%
Security personnel		1																1													2	91%
EMS cordinator	1																														1	93%
Client													1																		1	94%
IT support team																												1			1	96%
People who run simulations overnight	1																														1	97%
Ilogical people								1																							1	99%
H&S team												1																			1	100%
PERCEIVED CONTROL: What factors or circumstances do you feel make it ***easy*** for you to switch off appliances and lighting off when they are not in use at your workplace?																																
Acessible switches / controls	1		1	1	1		1	1	1	1	1	1	1	1	1	1	1			1				1		1			1		19	22%
Individual level of control		1				1		1	1	1					1			1	1	1			1		1			1		1	13	37%
Action not affecting surrounding people		1			1				1	1				1					1	1		1	1				1				10	48%
Centralised control			1		1						1		1		1		1	1					1	1		1					10	60%
Clearly labelled switches	1			1		1		1						1	1				1						1	1				1	10	71%
Delegation of responsibility	1				1							1					1													1	5	**77%**
Knowing if people are still in the office		1			1																								1		3	80%
Need to access work remotely										1											1				1						3	84%
Clearly labelled switches	1	1																													2	86%
Support from colleagues/management									1											1											2	89%
Forgetfullness			1												1																2	91%
Security																		1			1										2	93%
Automated controls																						1									1	94%
Make it a habit																											1				1	95%
Small impact one person has		1																													1	97%
Time consuming tasks									1																						1	98%
Changing behaviours																										1					1	99%
Takes time																												1			1	100%

Table 2 summarises the answers provided in the elicitation study. Answers for each question couplet were grouped to form a single set of answers (reversing the answers where applicable) and similar answers were grouped where appropriate. Each respondent is numbered from 1-30 illustrated by a single column. As observed, there is a large variation in the number of answers provided for each question by each respondent.

In order to account for 75% of all the beliefs stated, the answers were ranked in order of most often cited. The number of responses for a specific belief was summed and the percentage of the total number of responses was then calculated. This was done for each belief, in descending order, with the percentage value being calculated as a cumulative percentage so that the 75% target could be easily spotted. Once the cumulative percentage was reached, no further beliefs would need to be considered in the questionnaire development. For all three predictors of behaviour (attitude, social norm and perceived behavioural control), six beliefs were sufficient to account for 75% of the beliefs and are highlighted in grey in Figure 1.

Once the most significant beliefs were established, each of these was transformed into a question couplet, in line with guidance from Francis et al. (2004) as follows:

Attitude couplet: behavioural belief x outcome evaluation

e.g.: It is easy for me to switch off lighting and appliances when they are not in use: strongly disagree – strongly agree *(behavioural belief)* x Being able to conveniently turn off lighting and appliances is: very undesirable – very desirable *(outcome evaluation)*.

Subjective norm couplet: normative belief x motivation to comply

e.g.: Doing what my employer thinks I should do is important to me: not at all – very much *(normative belief)* x My employer would approve of me turning off lighting and appliances when not in use: strongly disagree – strongly agree *(motivation to comply)*.

Perceived behavioural control couple: control belief strength x control belief power

e.g.: The controls for switching off lighting and appliances are easily accessible: strongly disagree – strongly agree *(control belief strength)* x Accessible controls would make it easier for me to switch off lighting and appliances: unlikely – likely *(control belief power)*

Once each significant belief was transformed into a question couplet, the questionnaire was then developed, containing six groups of six questions (i.e. two sections for each predictor of behaviour, with every question having an equivalent couplet). The final questionnaire is illustrated in Figure 1.

Electricity Use Questionnaire

Age: _____ Male ☐ Female ☐

We are conducting a survey regarding electricity use in office buildings and would be very grateful if you could take a few minutes to answer this questionnaire. Please reflect on your own experiences in the office and mark (only) one answer per question. There are no right or wrong answers, so please tell us what you really think. In doing so please note that:

- **Appliances** include personal computers, monitors, printers (at your workstation and communal areas), personal heaters/fans, catering equipment e.g. kettles, microwaves, dishwashers etc.
- **Lighting** covers communal lighting in open plan areas as well as cellular offices and meeting rooms. Desk lamps should also be considered where applicable.

	Strongly disagree 1	2	3	4	Strongly agree 5
I am doing something positive to save energy by switching off lighting and appliances when they are not in use.	1	2	3	4	5
If I switch off lighting and appliances when they are not in use I will be helping my company to save money.	1	2	3	4	5
If I switch my computer off at the end of the day, it will take too long to reboot the following morning.	1	2	3	4	5
It is easy for me to switch off lighting and appliances when they are not in use.	1	2	3	4	5
If I switch off lighting and appliances when they are not in use I will be doing something positive for the environment.	1	2	3	4	5
Switching off lighting and appliances when they are not in use will prolong their lifespan.	1	2	3	4	5

	Very undesirable -2	-1	0	1	Very desirable 2
For me, saving energy at my workplace is:	-2	-1	0	1	2
Helping my company to save money is:	-2	-1	0	1	2
Switching off computers even though they take longer to reboot is:	-2	-1	0	1	2
Being able to conveniently turn off lighting and appliances is:	-2	-1	0	1	2
Doing something positive for the environment is:	-2	-1	0	1	2
Prolonging the lifespan of lighting and appliances is:	-2	-1	0	1	2

	Strongly disagree 1	2	3	4	Strongly agree 5
I have individual control over the lights around my workstation.	1	2	3	4	5
I can easily find the controls necessary to switch off lighting and appliances in my office.	1	2	3	4	5
The controls for switching off lighting and appliances are easily accessible.	1	2	3	4	5
I can turn off lighting and appliances when not in use without disrupting other colleagues.	1	2	3	4	5
I can switch off lighting and appliances through a centralised control system.	1	2	3	4	5
Responsibility for switching off lighting and appliances when not in use has been clearly delegated to one or more individuals.	1	2	3	4	5

	Unlikely -2	-1	0	1	Likely 2
Having individual control over the lights around my workstation would make it easier for me to switch them off.	-2	-1	0	1	2
It would be simpler to switch off lighting and appliances if I knew where the controls were located.	-2	-1	0	1	2
Accessible controls would make it easier for me to switch off lighting and appliances.	-2	-1	0	1	2
I would turn off lighting and appliances more regularly if I knew I wasn't disrupting my colleagues.	-2	-1	0	1	2
A centralised control would make it easier for me to turn off lighting and appliances when not in use.	-2	-1	0	1	2
Clear delegation of responsibility for switching off lighting and appliances would increase the chances of them being switched off.	-2	-1	0	1	2

	Not at all 1	2	3	4	Very much 5
Doing what my employer thinks I should do is important to me.	1	2	3	4	5
What my Facilities Manager thinks I should do is important to me.	1	2	3	4	5
The approval of my environmentally conscious colleagues is important to me.	1	2	3	4	5
I listen to what my Finance Manager wants me to do.	1	2	3	4	5
I do not want to inconvenience colleagues who work longer hours than me.	1	2	3	4	5
If a colleague is under pressure to get their work done, I am concerned that my actions might disturb them.	1	2	3	4	5

	Strongly disagree -2	-1	0	1	Strongly agree 2
My employer would approve of me turning off lighting and appliances when not in use.	-2	-1	0	1	2
The Facilities Manager would be happy if I turned off lighting and appliances when not in use.	-2	-1	0	1	2
I feel pressure from environmentally conscious colleagues to turn off lighting and appliances when not in use.	-2	-1	0	1	2
My company's Finance Manager pressurises me to turn off lighting and appliances when not in use.	-2	-1	0	1	2
Colleagues who work longer hours than me would be annoyed if I turned off lighting and appliances when I am finished for the day.	-2	-1	0	1	2
Colleagues who are under pressure to get their work done would disapprove if I turned off lighting and appliances when not in use.	-2	-1	0	1	2

	Much less 1	2	3	4	5	6	Much more 7
How much energy do you think you use compared to the average person *in this office*?	1	2	3	4	5	6	7
How much energy do you think you use compared to a person in an *average office*?	1	2	3	4	5	6	7

What time do you usually arrive at the office?	________
What time do you usually leave the office?	________

Thank you for your time!

This questionnaire will be collected from your desk. If you have any additional comments, please feel free to write them on the back of this sheet.

Figure 1: Occupant behaviour questionnaire