

Energy Consumption in Non-Domestic Buildings based on Empirical Data

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ABSTRACT

The electricity demand data for a variety of buildings throughout the UK has been made available for analysis. This consists of half hourly resolution data spanning several years for 48 schools (with a mixture of secondary, primary and specialised secondary) and two office buildings, allowing key trends and patterns in energy use to be identified. These trends can include differences between annual profiles, differences between winter and summer months, and differences in weekday and weekend energy use. Additionally, the effect of other variables such as climate, user behaviour and general building data on the building's energy consumption can be investigated.

A database of half hourly school energy demand data, with corresponding building details has been set up and a preliminary analysis performed. Alternative methods of pattern recognition in non-domestic energy usage are discussed, and the variables necessary to calibrate this information are evaluated. This allowed the possibility of creating 'generic' electricity demand profiles for each category of school in each season, leading to a more detailed energy performance benchmark table.

Understanding the energy demand, both electricity and gas use, of a building can help the issue of determining how and when energy is used in a day, week, month or year. Only after this knowledge has been gained can energy saving measures be successfully applied and, in turn, can the energy consumption of the non-domestic sector be reduced.

DEDICATION

This thesis is dedicated to Nicola and Lily-Rose

DECLARATION STATEMENT

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Chapter 1- INTRODUCTION

This thesis is concerned with energy consumption of non-domestic buildings. Energy consumption, despite efforts to contain its growth, is continually increasing throughout the world. Buildings are a major contributor to this global increase in energy consumption, with the non-domestic building sector making a marked contribution to this increase. Energy consumption associated with non-domestic buildings represents 11% of the UK's total energy consumption, 11% of consumption in Europe and 18% for the USA's (Pérez-Lombard *et al.*, (2008). In order to determine how the energy consumption associated with the non-domestic sector can be reduced, it is first necessary to understand how buildings consume energy. Insight into how buildings consume energy can be obtained by investigating and defining a building's power demand profile. Once defined, this in turn can highlight periods of power wastage, and hence identify where energy saving measures can be successfully applied. In addition, benchmarking can also be used as it is a powerful energy efficiency tool which allows the annual energy consumption of a building to be compared with a predetermined set of energy benchmarks. From the subsequent comparison of available/published benchmark values against calculated values how energy efficient a building is can be defined. Measures can then be taken to improve the buildings efficiency to either match or improve on the published benchmark value.

However there are several recognised issues associated with the current published energy performance benchmarks. A key issue relates to how representative these benchmarks are in general. The non-domestic building sector has a wide range of building stock, with varying construction age, building construction type and how each building is used. One way to overcome the variation in building types is to focus on a specific sector of non-domestic building, such as schools. However, even with this approach, schools show an array of building sizes, and marked variation in how the schools are used for example, high schools (secondary schools) versus primary schools. Thus, having one set of energy performance benchmarks, for instance a 'school benchmark', may not be representative of schools in general or of the different type of schools in this building sector. As the energy performance benchmarks could have been constructed based on a small sample of high schools, and hence may prove insufficient when being used for other types of schools, such as primary schools.

Another issue associated with current benchmarks is that they do not account for key factors, such as age of the building, type of heating, number of pupils, location and

the impact that the seasons can have on energy demand. For example, an electrically heated primary school located in the north of Scotland cannot be compared with a gas heated high school located in southern England, due to difference in size, and lower demand from regional temperature differences. Additionally, changing seasons (and hence changing weather conditions) generally result in a higher energy demand in winter than in summer, which is neglected in total annual benchmarks. Applying an energy saving measure that is only suitable in a low demand period (such as summer), for instance, may have only a small impact on the total energy consumption of the building.

Improved energy performance benchmarks that account for building type, category, age, location and season should overcome these recognised issues associated with current available/published identified benchmarking. In addition to the creation of new energy benchmarks, the generation of typical or 'generic' power demand profiles (representing the power demand over a 24 hour period) would make it possible to demonstrate and/or predict a building's power demand. With this approach, key building information (size, type, age, location, and season) would be accounted for, and both a power demand profile and an associated performance benchmark representing the correct building type, age and season generated. This would allow building operators to predict their building's power demand, and hence determine how energy saving measures or renewable energy devices can impact on a buildings power demand (and in turn its energy consumption).

This research project assessed whether or not energy data can be generalised in order to predict energy consumption. Four main questions were addressed;

1. If energy data is analysed at a finer time resolution does this approach provide a clearer insight into how buildings consume energy?
2. Can the power demand of non-domestic buildings be generalised, and hence 'generic' power demand profiles representing typical power demand be generated?
3. Using the 'generic' power demand profiles, can 'generic' energy performance benchmarks be generated?
4. By extension, can 'generic' power demand profiles and performance benchmarks be generated for thermal demand, and for other types of buildings?

The literature review (chapter 2) focused on determining current energy trends, and examined current benchmarking methodologies, power demand profile analysis and energy saving measures. This chapter investigated how power demand profiles can be

analysed and in turn defined what information was necessary to develop ‘generic’ demand profiles and benchmark data. The literature review leads into the data collection chapter (Chapter 3). This chapter discusses how the building energy databases were created (for both electricity and thermal), as well as the other data (building details and weather data) used in conjunction with the energy data. Chapter 3 outlines how the collected data was organised into different databases. Although this research project collected energy data on a wide range of buildings, the majority of the data collected was electric power data, with a small percentage of thermal demand data. Additionally, the scope of this research project was largely restricted to schools, due to limitations of available data. Despite a small investigation of two offices, it is anticipated that future investigations will extend the work to include other non-domestic buildings. Chapter 3 also discusses each of the collected databases; School – electricity, School – gas and Office – electricity.

In addition, Chapter 3 discusses how the data was analysed, the analysis program developed and each analysis section of the program, as well as the generated output files. It finally discusses how the school electrical and thermal data was filtered to ensure that a typical view of energy demand was gained, including the removal of school holidays and any abnormal profiles.

The results were separated into two key sections; initial analysis (chapter 4) and ‘generic’ profiles (chapter 5). The initial analysis focuses on determining which data normalisation factors have an important impact on power demand (construction age, floor area, pupil numbers, and category) and how analysing average power demands can provide an insight into how and when buildings demand power. Chapter 5 additionally introduced school categories to the school databases to establish the differences between high schools, primary schools and specialised high schools. It then focuses on school electricity distribution board data and how the use of this more detailed data can provide a more accurate insight into what systems contribute to the rise and fall in power demand within a school. The focus of this chapter then changes to investigating power demand in two office buildings. The effect of two key weather variables (outside temperature and global solar radiation) on power demand is described. Lastly, the thermal data (gas demand) for several schools were analysed. This analysis focused on average gas demand profiles and investigated if thermal demand of schools can be generalised, to produce ‘generic’ thermal demand profiles.

Chapter 5 outlines how generic profiles and energy performance benchmarks can be constructed. This chapter investigates all school demand profiles, and identifies several

key trends between each school type and the impact of seasonal changes on the power demand. Chapter 5 also discusses the generation of ‘generic’ power demand profiles for each school type, as well as corresponding annual benchmarks.

Chapter 6 and chapter 7 discuss the results and implications (separated into initial analysis results and generic analysis results), as well as any issues and possible improvements in data collection, and methodology. The final chapter, chapter 7, discusses the findings of the research project and places the results in context to the four questions that formed the basis of this research project.

Chapter 2 LITERATURE REVIEW

This chapter overviews current research on energy consumption of non-domestic buildings, and is separated into several key sections. These sections include current energy consumption and trends, benchmarking methodologies, power demand profile (analysis and capture), and energy saving measures. Each section will be addressed, and any key results or short comings in the previous research discussed.

2.1 Background Energy Usage and Regulations

This section discusses current energy consumption, investigating global consumption, UK consumption and finally focusing on non-domestic energy consumption. It also addresses current energy regulations within the UK and the EU on tackling the continual growth of energy consumption. Lastly, this chapter will investigate the breakdown of energy usage by different end use categories for both office buildings and school buildings.

2.1.1 Current Energy Usage

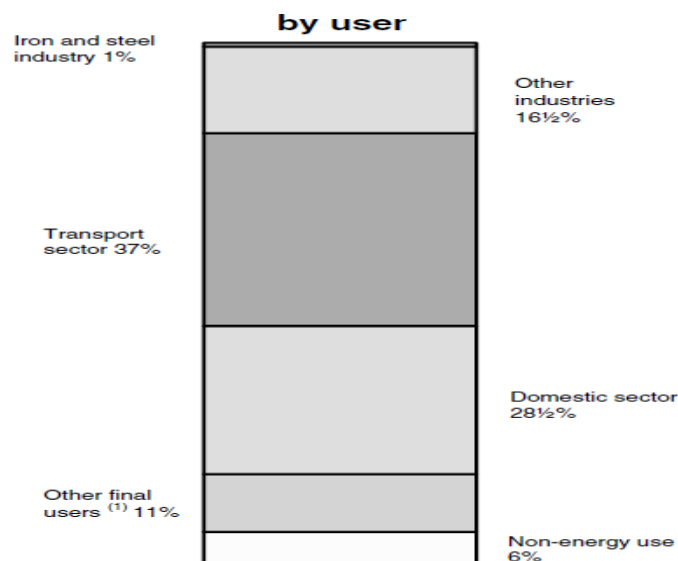


Figure 1 - Energy Use By Sector, Department of Energy and Climate Change, (2010)

In 2007 the UK consumed 157.8 million tonnes of oil equivalent (Mtoe) or alternatively 1,835TWh of energy (Department for Business Enterprise and Regulatory Reform, (2006)). In terms of electrical use, the total energy consumption was 407,265GWh. To better understand how energy is used in the UK, the energy consumption has to be disaggregate into the different sectors. According to Steemers, (2006), in 2006, there was the following breakdown; domestic consumption: 29.4%,

transport consumption: 37.1%, industry consumption: 20.8% and “other” consumptions: 12.7% of total UK energy consumption. The percentage of energy consumption associated with only buildings in relation to total energy consumption is 42.3% (Steemers, (2006)). It can be assumed that the ‘buildings’ mentioned in Steemers, (2006) consists of both domestic and non-domestic properties.

Figure 1 highlights the proportions of total energy use by key sectors. The results are representative of 2010, where as the results stated by Steemers, (2006) are based on data from 2006. It can be observed that little has changed between the two datasets. Domestic energy consumption has decreased from 29.4% down to 28.5%, other consumption has decreased from 12.7 to 11% and industry has decreased from 20.8% to 16.5%. The decrease in demand from the domestic sector could be due to increasing energy efficiency in the home. The change in industrial demand could also be the result of increased efficiency, or due to the recession (decreased output). It is unclear what “non-energy use” is in Figure 1.

In 2003, non-domestic buildings accounted for 11% of total energy consumption in the UK, 11% in the EU and 18% in the USA Pérez-Lombard *et al.*, (2008). The similarity between UK and EU consumption is probably due to similar work habits, daylight hours and climate, while the USA’s higher proportion may be due to the higher presence of air conditioning or to a different proportion of offices to other types of buildings.

Within the non-domestic sector, offices account for 17% of non-domestic energy consumption and 2% of total energy consumption of the UK, whereas in the USA offices account for 18% and 3.2% respectively Pérez-Lombard *et al.*, (2008). As mentioned previously, the differences in the UK and USA figures could be due to the proportional differences in the number of offices to other sectors. Although this thesis will not thoroughly investigate or analyse USA consumption data, it is beneficial to observe another country’s energy consumption habits and observe any differences.

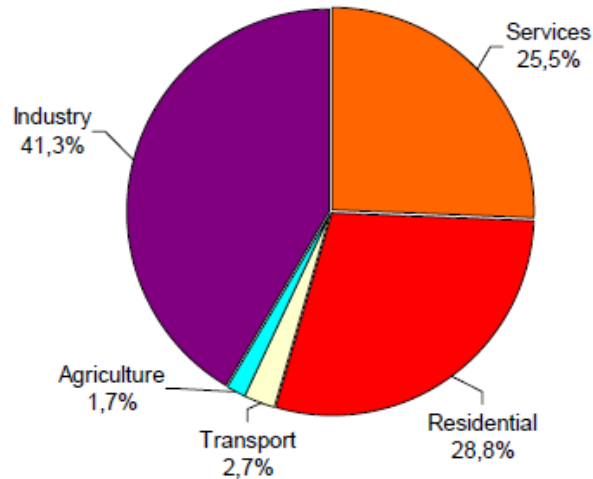


Figure 2 - Breakdown of Energy Usage in Europe Bertoldi *et al.*, (2007)

The breakdown of total energy usage by sector in Europe is shown in Figure 2. The figure depicts the differences in each key sector percentages when compared with those discussed in Steemers, (2006) and Department of Energy and Climate Change, (2010). It can be seen that the residential proportion is very similar (~28%), the transport sector is 2.7% and the industry proportion is 41.3%. The transport and the industry percentages are very different compared with Steemers, (2006) and Department of Energy and Climate Change, (2010)/Department of Energy and Climate Change, (2006). One main reason for the difference is that Steemers, (2006) and Department of Energy and Climate Change, (2010)/Department of Energy and Climate Change, (2006), and the work by the Joint Research Council (Bertoldi *et al.*, (2007)) is that the results shown in Figure 2 represent the entire EU. The EU includes several countries that still have a large industrial presence, such as car industries and other goods, compared with the UK, that has very little. The similarity in domestic energy consumption will be due to the similarities in user behaviour in the home in the EU and in the UK. It is unclear from Bertoldi *et al.*, (2007) what the ‘services’ sector actually includes.

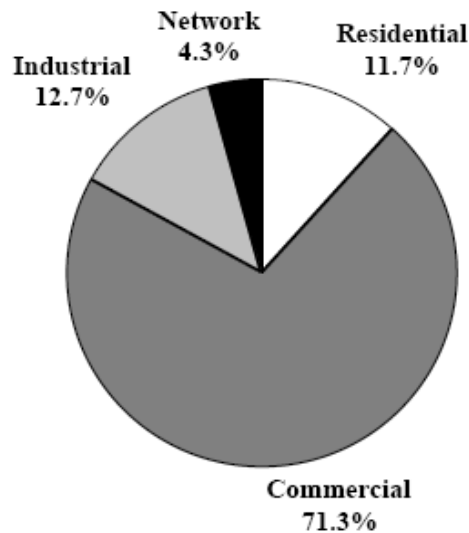


Figure 3 - Breakdown in Energy Use, Kawamoto *et al.*, (2004)

An additional basic breakdown of total energy use by sector is shown in Figure 3 representing the Japanese market. The figure shows that the commercial sector is the largest consumer, sharing 71.3% of the total. It should be noted that this breakdown represents a Japanese city, where energy use can be different to UK energy consumption. The increased use of air conditioning in offices and other non-domestic buildings may result in a larger proportion of energy being associated with the commercial sector.

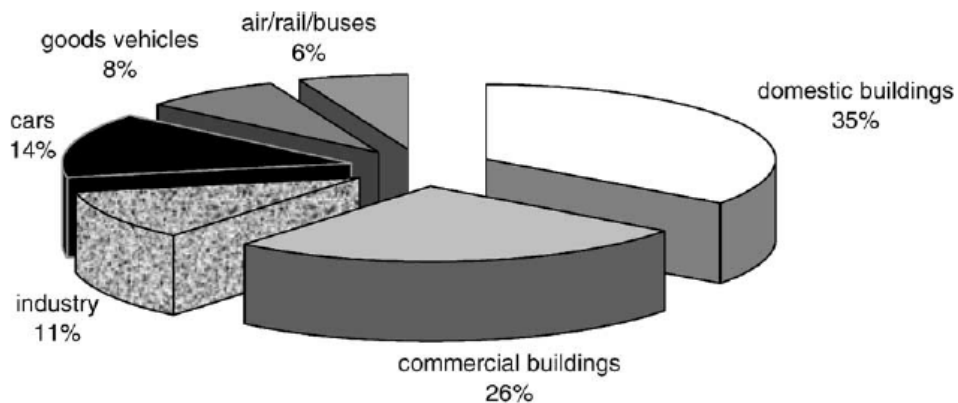


Figure 4 - Energy Breakdown of London, Steemers, (2003)

Similarly with the breakdown of energy use presented in Kawamoto *et al.*, (2001), the energy distribution of London is discussed in Steemers, (2003), see Figure 4. This breakdown shows that commercial buildings only represent just over a quarter of total energy usage in London, and that residential buildings are the largest proportion. This could be due to London being a fairly congested city, with a population of around 7.83 million (Bain, (2010)). Steemers, (2003), stated that in London, the proportion of buildings to transport is 2.2:1, though there is no mention of what constitutes as

‘buildings’, whether it is residential, industrial or commercial. A key difference between the breakdowns shown in Figure 3 and Figure 4, is that the chart presented by Steemers, (2003) represents all areas of energy use including transport. Figure 7 appears to remove any form of transport, hence the different proportions. It should also be noted that Figure 8 represents London’s total energy consumption, and may not represent other cities in the UK, due to London being a fairly unique city.

Another key area in the non-domestic sector is education. Dimoudi *et al.*, (2009) believed that energy awareness in schools is extremely important because the children that are being taught are the next generation. Primary schools in the UK typically consume 119KWh/m²/yr of energy (Dimoudi *et al.*, (2009)). The UK is one of few countries that have set energy benchmarks for schools. A target of 110KWh/m²/yr is considered as an ideal or “good practice” value Hernandez *et al.*, (2008).

2.2 Current Energy Trends

Total energy use in the UK has increased from 200 Mtoe (2,326TWh) in 1985 to 245Mtoe (2,850TWh) in 2001 (Department for Business Enterprise and Regulatory Reform, (2008)). There will be a point in the future where the demand for energy will outstrip the supply. Developed nations consumed about 3200Mtoe (37,216TWh) in 1970 and around 5500Mtoe (63,965TWh) in 2005, (Pérez-Lombard *et al.*, (2008)). According to Pérez-Lombard *et al.*, (2008), by 2025, the developed nations will consume an estimated 7000Mtoe (81,410TWh) of energy. If the developing nations are studied, in 1970 they consumed an estimated 900Mtoe (10,467TWh) of energy whereas in 2005 an estimated 4200Mtoe (48,846TWh) was consumed (Pérez-Lombard *et al.*, (2008)). Pérez-Lombard *et al.*, (2008) estimated that the developing nations will consume 7500Mtoe (87,225TWh) by 2025. The total energy consumption has been increasing at a rate of 1% per year for the last decade Kelly, (2006), with electricity increasing at a rate of 2% per year. If electricity continues to rise at this rate, by 2010 the total will reach 30TWh (Kelly, (2006)).

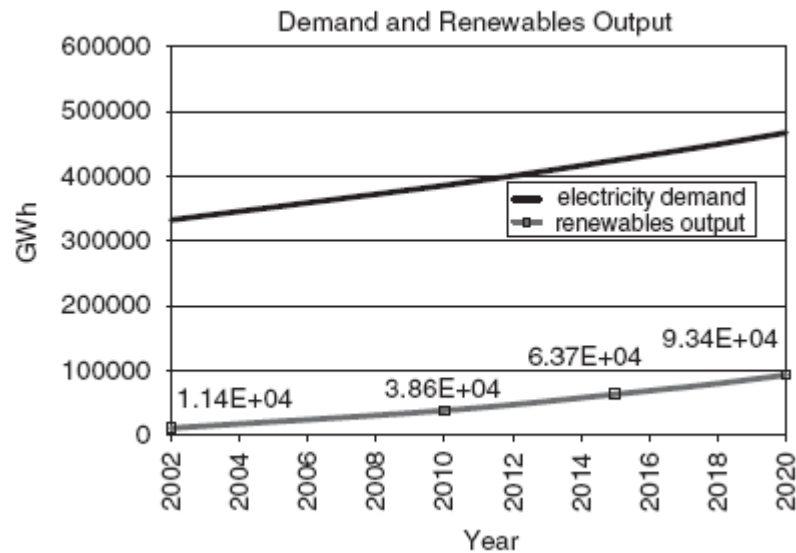


Figure 5 - Predicted Electricity Growth, Kelly, (2006)

Figure 5 demonstrates the predicted UK annual increase in electricity consumption stretching from 2002 to 2020. According to the figure, UK electricity will increase to 480000GWh (480TWh) by 2020.

If the UK's non-domestic sector is investigated and focused solely on the service sector, an insight of how energy in the UK is consumed can be constructed. The service sector, according to the Department for Business Enterprise and Regulatory Reform, (2008), can be divided into two separate classes; a) public sector and b) private commercial. The public sector includes areas such as education, health and government. Private commercial includes building such as hotels and retail. In 1970, the combined consumption of both private and public services was around 16,000Ttoe (thousands of tonnes oil equivalent), or alternatively 186TWh. In 2001, this combined consumption was around 20,000 Ttoe (236TWh) (Department for Business Enterprise and Regulatory Reform, (2008)). The service sector in 2001 accounted for 13% of total UK energy demand. It is interesting that the industrial sector has seen a sharp decline in energy use, by around 44%, since 1970 Kelly, (2006). This decline is most likely due to the decline in manufactured goods (cars, electronics) hence the reduction in factories.

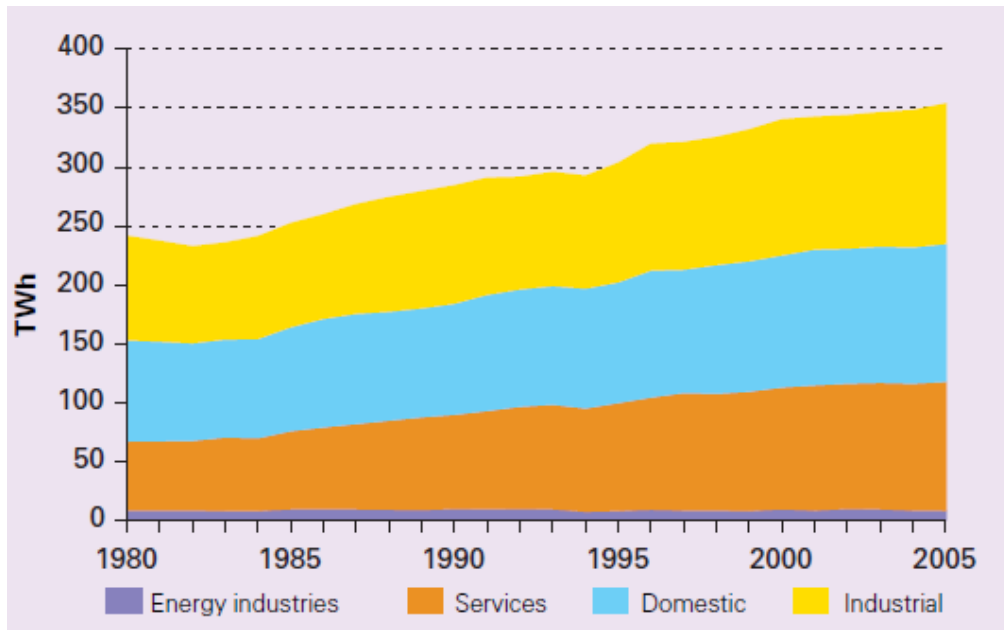


Figure 6 - Trends in Energy Consumption by Sector Department for Business Enterprise and Regulatory Reform, (2006)

Building energy consumption is currently rising at 0.5% per year in the UK and 1.5% in the EU and will reach 34% of total energy use by 2028 (Pérez-Lombard *et al.*, (2008)). Figure 6 demonstrates the energy consumption of different sectors from 1980 to 2005. From 1980 to 2005, the consumption associated with the services sector increased from 60TWh to 100TWh (or 66%), and the domestic sector increased from 90TWh to 200TWh (or a 122% increase). Lastly, the industrial sector increased from 100TWh to 150TWh (or a 50% change). The figure also highlighted that the energy industries sector has had varying energy consumption over the 25 year period. Figure 6 is useful in highlighting how energy consumption within the UK is continually rising, and that the rise is driven mainly by the increase in all three identified sectors.

The predicted future energy consumption figures provided by both Department for Business Enterprise and Regulatory Reform, (2008, Pérez-Lombard *et al.*, (2008), and Kelly, (2006) should be treated with care. The 2028 built environment figure is based on the current trend, i.e. if there are no changes in consumption behaviour or energy efficiency.

2.3 Carbon Saving and Reductions

The extent of the problems associated with increased energy use, are highlighted when current and predicted CO₂ emissions are investigated. As energy usage increases, it can be argued that generally carbon emissions also increase. It is assumed that the increase in energy is associated with the increase burning of fossil fuels. Other power sources such as nuclear and renewable sources of power should not have an impact on

total carbon emissions. Mortimer *et al.*, (1998) argues that global warming is one of the biggest challenges to face mankind and hence changes must be made. It is also stated that any possible solution would need change in human behaviour and a change in current activities. This essentially means that it is up to the consumer, of both non-domestic and domestic buildings (and other industries/areas) to modify their own energy consumption. The problem with this is that it is very difficult to change a person's behaviour or habits, especially if you rely on common sense or good faith. Mortimer *et al.*, (1998) also states that any energy saving or efficient solutions would provide both financial and environmental benefits. The financial benefits would be saving money due to the reduction in energy demand and environmental benefits would be the reduction in carbon dioxide.

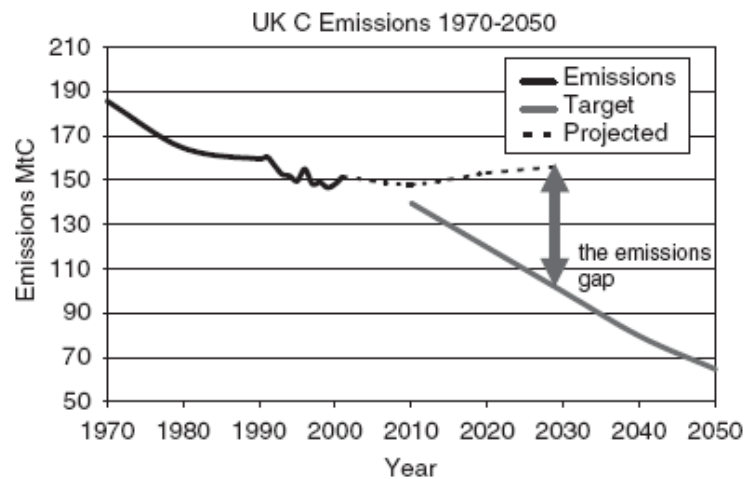


Figure 7 - UK CO₂ Emissions Kelly, (2006)

The UK has set out to reduce its carbon emission targets by 60% by 2050, ahead of the Kyoto Protocol's recommendation of 12.5% by 2012 (Kelly, (2006)). Figure 7 highlights the CO₂ emissions from 1970 to 2000, and the predicted emissions beyond 2000. Additionally, the figure demonstrates the 60% reduction target and the subsequent emissions gaps. The chart suggests that by 2020 carbon emissions will continue to rise, further increasing the emissions gap. Figure 7 also highlights that carbon emissions have actually decreased from the 1970's until 2000, where emission started to rise slowly. This could be due to the introduction of nuclear power and gas turbine power stations, as well as domestic gas use. The savings from the 1970's to 2000 are being cancelled out as the population increases and demand for energy increases. Kelly, (2006) stated that at this rate of increase in CO₂, the UK will miss both the Kyoto targets and its own targets.

2.4 Energy and Energy Usage Regulations

According to, Hernandez *et al.*, (2008), the most significant energy regulation is the EU Energy Performance in Buildings Directive (EPBD). The main objective of the directive is to promote awareness of energy performance in buildings. This is achieved by providing data on “good practice” benchmarks for energy usage. Hernandez *et al.*, (2008) states that there are several countries that have set ideal benchmarks for certain sectors including the UK. However there are several countries or member states within the EU that do not have the capability to produce benchmarks. Hernandez *et al.*, (2008) argues that some member states may not have the access to energy models or have the ability to calculate energy performance benchmarks. Another reason could be that several member states may not have a resource of previous energy data. This work done by Hernandez *et al.*, (2008) highlights the problem with providing legislation without ensuring that all member states can comply.

2.5 Energy breakdown in buildings

The breakdown of energy in offices, in this context, is the disaggregation or division of total energy usage into the individual appliance usage. There is a wide range of buildings with non-domestic stock, and hence different uses of energy. The following section describes the breakdown in energy use in a selection of key buildings studied in this research.

2.5.1 Breakdown in Offices

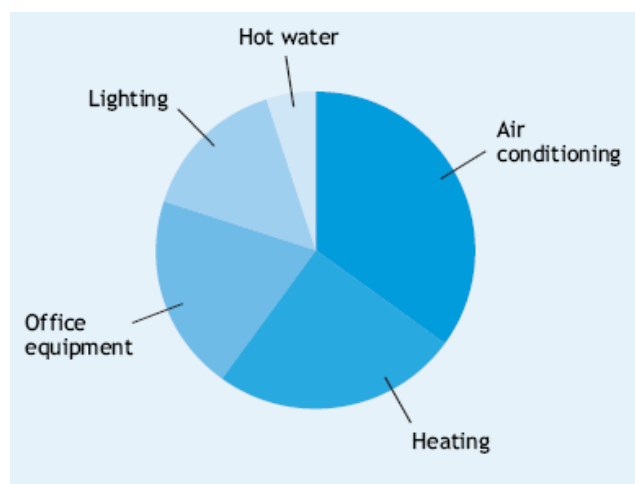


Figure 8 - Breakdown in Energy Use Carbontrust, (2003)

It has already been stated that a small percentage of UK energy consumption is related to office energy use. The problem of having only one figure or percentage for energy use is that it primarily indicates what the annual total use. Ideally a breakdown

of where energy is being consumed (i.e. by end use) is required. According to Mortimer *et al.*, (2000), a typical office can have the following energy consumption percentages; heating is 56.7%, light is 14.8%, computers is 6.9%, catering is 3.%, fans are 2.1%, small power equipment is 1.9% and finally “other” usage is 4.5%. The energy breakdowns are the result of statistical estimation and analysis, not actual measurements of data taken from previous building energy surveys. Mortimer *et al.*, (2000), suggests that the subsection of “heating” is both hot and cold climate control, thus could be also called Heating Ventilating and Air Conditioning (HVAC). The breakdown is for a statistical “typical” office building can be seen as a problem.

Figure 8 demonstrates a basic breakdown of an office’s energy usage by end use. According to the report, 20-40% of a buildings total energy use is the result of heating, 15% associated with electrical equipment (IT), and the remainder associated with lighting, hot water and air conditioning. Although not very detailed, Figure 5 visually provides a quick understanding of energy use. One disadvantage is that the figure is based on an air conditioned office, which does not represent the full office building stock.

For accurate energy analysis, further information would be required on the specific properties that contribute to a “typical” office building. One of the most significant properties would be whether the building is naturally ventilated or if the building has air conditioning. There can be a significant energy consumption difference between a small office, that has a small ventilation system, compared with a large multi-floor office that has a large AC (air conditioned) system. Similarly, a breakdown in Steemers, (2003), shows basic office energy consumption, as shown in Figure 9. Steemers, (2003), stated that an air conditioned office has a breakdown as follows; lighting is 34%, heating is 22%, fans/pumps are 30% and refrigeration is 14%. As with Mortimer *et al.*, (2000), the energy breakdown is for a “typical” office and may not be applicable to individual buildings.

When the energy breakdown values in Mortimer *et al.*, (2000), and Steemers, (2003), are compared, several differences are made apparent. One reason for the discrepancies is how the breakdown percentages were derived. In the case of Steemers, (2003), the breakdown represents an air conditioned office with the demand from office equipment (computers, photocopiers, etc) removed. The result of removing this portion of energy demand (i.e. small power) could be the increased percentage of the other sectors. Another problem between Mortimer *et al.*, (2000), and Steemers, (2003), is defining basic sectors of individual energy consumption. In Mortimer *et al.*, (2000),

heating accounts for over 50% of an office’s energy consumption. As mentioned previously, we have assumed that “heating” relates to both hot and cold air ventilation. In Steemers, (2003), air conditioning is represented by the summation of “fans/pumps” and “refrigeration”. The “heating” section is completely independent from the air conditioning consumption. These problems underline why it is difficult to use theoretical or statistically derived energy percentages for use as benchmarks.

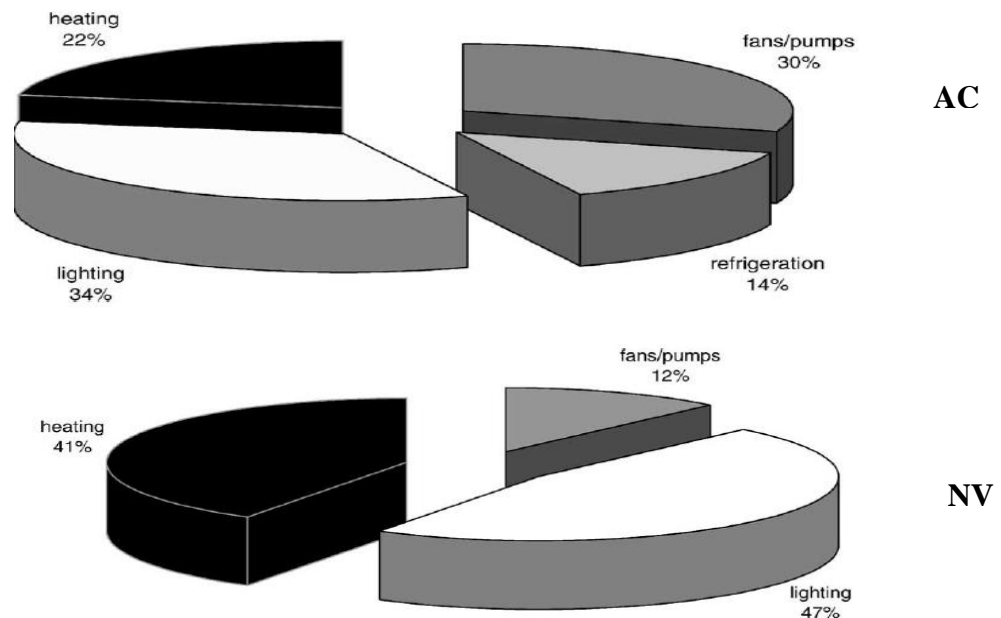


Figure 9 - Breakdown of Office Energy Consumption, Steemers, (2003)

Both the Carbon Trust (Carbontrust, (2003)) and Steemers, (2006), provide energy breakdowns of different types of buildings. Steemers, (2006) provided only two simplistic building energy breakdowns which represented both an air conditioned building and a naturally ventilated building. Although there are only two models, the provided breakdowns reinforce the energy consumption differences between the two models. The main consumption changes are in “fans/pumps” and “refrigeration” sectors. As discussed in Steemers, (2003), these two sectors relate to air conditioning. A more detailed sample of office buildings and their subsequent energy consumption can be found in the Carbon Trusts publication (Carbontrust, (2003)). There are four models used in Carbontrust, (2003) which are as follows; a) naturally ventilated, b) naturally ventilated open plan, c) air conditioned standard and finally d) air conditioned prestige. A key advantage of using Carbontrust, (2003) for estimated benchmarks is that there are both typical and “good practice” values for each of the different types of buildings. This could be useful finding a similar building and the subsequent energy breakdown, as discussed in later sections.

Similarly work carried out by Chen *et al.*, (2006) provided an energy breakdown chart for a large commercial building in Shanghai, shown in Figure 10.

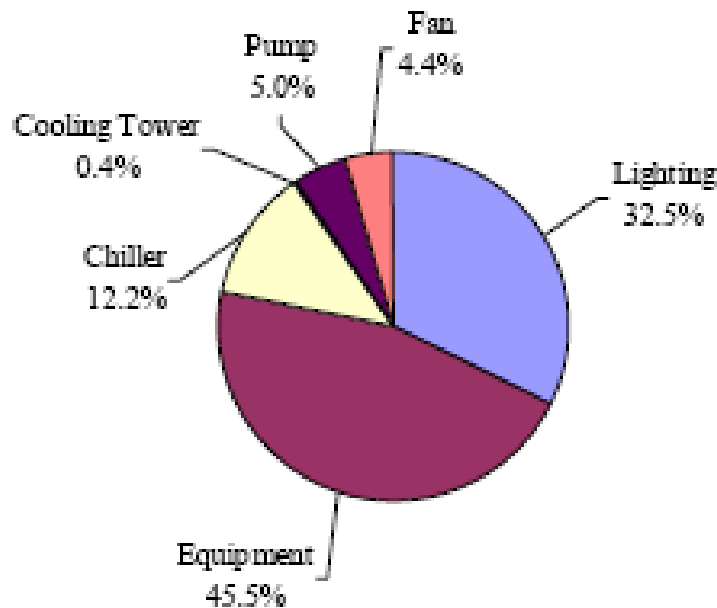


Figure 10 - Office Energy Breakdown Chen *et al.*, (2006)

The methodology for collecting the data is discussed in later sections. The results from Chen *et al.*, (2006), are useful in showing the differences, if any, in energy consumption of offices in different climate zones. Similarly to the comparison between Steemers, (2006), and Kawamoto *et al.*, (2004), climate can play an important role in building energy consumption.

Although not entirely useful to energy analysis in the UK, work carried out by Lam *et al.*, (2004), demonstrates the breakdown of energy usage of offices in sub-tropical climates, focusing on Hong Kong. The project involved taking a selection of buildings in Hong Kong and monitoring the energy usage. Other data such as behaviour of electrical and heating equipment, working hours and lift usage were also recorded. One problem that arises from the study was that it would be very difficult to accurately measure or predict how workers interact with an office environment. The results from the study (as a percentage of total) are as follows; lighting was 27.4%, air conditioning was 47.5%, electrical equipment was 21.8% and escalators/lifts were 3.3%. These results are similar when compared with Steemers, (2003).

2.5.2 Breakdown in Schools

To gain a slight insight to how energy is being used the breakdown in total energy use can be investigated. Figure 11 (a) highlights the energy usage per power

source and by appliance usage or end user. From the figure, it can be seen that the main end user is space heating (58%), which would be either gas or oil boiler based systems. The other main users are hot water (15%), lighting (8%) and catering (8%). When this compared with the associated costs, Figure 11(b) the proportions have changed. This is due to the cost of a unit of gas being cheaper than a unit of electricity. Although space heating (fossil) still accounts for 45% of costs, lighting (that was only 8% of total energy consumption) now counts 20% to total energy costing. Total breakdowns in energy use are very useful in determining where potential energy savings could be undertaken, and the resulting cost savings.

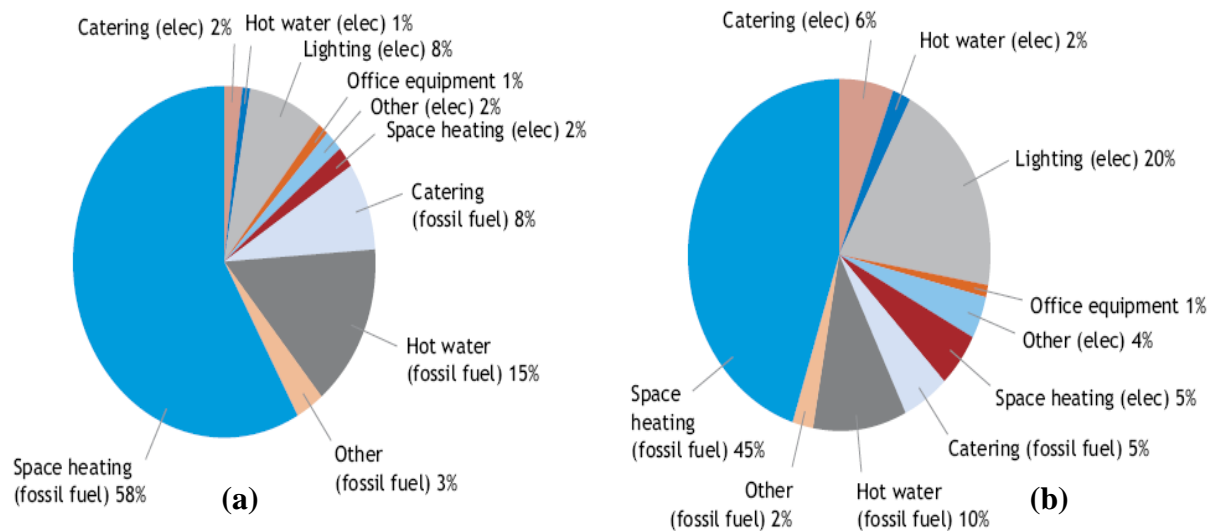


Figure 11 - Breakdown in School energy Use Carbontrust, (2010b)

One disadvantage to the approach shown in Figure 11 is that it represents a very generic school and it is unclear whether this school is a primary or secondary school. It could be assumed that the energy use distribution would vary between the two types of schools. Primary schools would not have the same level of IT support, classroom technology or room use. Additionally, the heating systems may be different, as smaller primary schools may rely on electric space heating, opposed to fossil fuel boilers. In large secondary schools it may be impractical to use electric space heating. Ideally two separate breakdown charts would be needed to determine if there are any differences between primary and secondary schools, and the size of the differences. An additional energy breakdown chart would help explain the differences between schools types (i.e. primary, secondary).

Another potential issue is that it is unclear how swimming pools are included into this breakdown. Swimming pools can cost the school over £30,000 a year (Carbontrust, (2010b)), meaning a sizable proportion of energy use is associated with pools, and hence have to be accounted for.

2.6 Energy Performance Benchmarks

Energy Performance Benchmarks (EPB) are a useful tool in allowing quick comparison of building energy use per annum against preset standards.

“Using the established benchmarking curves developed as a result of the study, the total energy saving potential of a building can be calculated using the total/landlord/tenant energy performance benchmarking curves” Majid Haji-Sapar, (2005)

“Benchmarking is defined as a continuous process during which processes and methods of operational functions as well as products and service’s of one’s own company are measured against a benchmark, i.e. the maximum achievable performance” Stoy *et al.*, (2006).

Energy benchmarks that are categorised down into ‘good practice’ or efficient, and ‘typical’ or average groupings further detail an idea into how energy efficient a building is, can be determined. Energy benchmarks are also a guide when designing and constructing buildings, as the benchmarks can be used energy performance goals. T

This section discusses current benchmarks for both schools and offices, as well as basic benchmarking methodology.

2.6.1 Energy Benchmark Methodology

The methodology used to determine energy performance benchmarks for buildings is extremely important. Accuracy and repeatability are essential as the methodologies have to be accurate enough to provide acceptable benchmarks, and carry this accuracy across a wide range of buildings. The following section discusses several benchmarking methodologies, investigating the advantages and disadvantages of each methodology.

Chung *et al.*, (2006), investigated how benchmarks (as used in Energy Performance Certificates) were created. The aim of Chung *et al.*, (2006), was to establish energy efficiency benchmarks and find any relationship between energy usage and external factors. There are several ways of calculating energy efficiency benchmarks, according to Chung *et al.*, (2006); a) energy normalisation, b) linear regression and c) residual distribution. Energy normalisation by floor area, involves dividing the total energy use of a building by the total floor area, resulting in kWh/m²/yr. Chung *et al.*, (2006), stated that this is the typical approach to establishing energy efficiency benchmarks or ‘indicators’. The problem with this approach is that it

does not take into account any other variables, other than floor area and energy consumption. This could in turn result in inaccurate efficient benchmarks.

Linear regression is a method of calculating the efficiency benchmark by incorporating several other variables. Within this method, the average value within several studied buildings is not a suitable method for benchmarking. A more accurate method is using a distribution standard errors table. Chung *et al.*, (2006), stated that the EnergyStar modelling software uses a “multivariate linear regression distributional benchmark table”. Residual distribution uses the residuals from a regression model, which Chung *et al.*, (2006), defined as being the difference between the predicted energy use intensities (EUI), and the actual EUI. This residual can be considered the ‘inefficiency’ of the building. If the residual is negative then the building uses less energy than originally predicted, and vice-versa.

There are three steps in the benchmarking method; a) climate adjustment of EUI by degree day normalisation, b) regression model building and c) benchmark table construction. Chung *et al.*, (2006), defined the ‘degree day’ as the difference in the daily mean temperature value and a predefined base temperature. The regression model is used to determine any relationships between the normalised EUI and any of the buildings characteristics. Lastly, Chung *et al.*, (2006), defined the benchmarking table based on the percentiles of the final data. The use of degree day normalisation would require a weather database (or at least a temperature database) at sufficient resolution to match the data.

To demonstrate the benchmarking process, Chung *et al.*, (2006), discussed a study into supermarkets. Thirty supermarkets were selected at random and key building details recorded. The chosen supermarkets varied in size and design; however all were detached buildings with air conditioning. Chung *et al.*, (2006) focussed on nine variables that would be used in the linear regression model. These were as follows; a) building age, b) floor area, c) operational schedule, d) number of customers, e) occupants behaviour, f) indoor temperature set point, g) chiller type, h) lighting equipment, and i) lighting control. The operation schedule is defined by Chung *et al.*, (2006), as the hours of operation per annum. The occupant’s behaviour is assessed using a points or rating score. The point system is broken down into assessable categories, which are as follows; a) turning off lights when not in use, b) turning off AC when not in use, c) turning other equipment when not in use, d) setting energy targets, e) having a respectable energy audit, and lastly f) planning regular maintenance of

equipment. The last detailed variable is the indoor temperature set point, which is defined as the temperature the AC unit has to maintain.

There are several problems with the variables discussed by Chung *et al.*, (2006). The first is the occupant's behaviour factor. This is a non-quantitative factor; hence a precise scaling or points system cannot be introduced or used. It would rely on the assessor's discretion on how many points were awarded for each sub-category. It could be argued that the system is fair if the same assessor is used throughout the survey. If not then there could be several discrepancies throughout the investigation. Another problem with the occupant's behaviour factor is that how the points are awarded, i.e. if there is a point scaling or just one point for one category. The last issue is with the numbers of customers per annum factor. Careful examination is needed of where the analysed data was recorded, whether it is based on a statistical approach or if check-out sales have been used. These variables could be used easily to produce regression models for other buildings, although the 'number of customers' variable appears to be best suited for supermarkets and shops.

The investigation on benchmarking carried out by Chung *et al.*, (2006), provided useful information on how linear regression can be used to form benchmarking tables. Chung *et al.*, (2006) provided a basic methodology outline and the derived linear expression for benchmarking. As already stated there were several issues with the factors used in the linear regression. Additionally details on how the linear expression was actually derived were omitted, and any assumptions made during the derivation were also not discussed. However, the idea and concept behind benchmarking energy efficiency were successfully conveyed by Chung *et al.*, (2006).

Work by Hernandez *et al.*, (2008) aimed at investigating and producing energy benchmarks in Irish primary schools. In the EU, French primary schools average 197kWh/m²/yr, Greek schools consume 57kWh/m²/yr and Irish primary schools consume 119kWh/m²/yr. Hernandez *et al.*, (2008) used the 'Good Practice Guide 343 (Carbontrust, (2008)) to establish that the typical value for UK primary schools is 157kWh/m²/yr whereas the best practice value is 110kWh/m²/yr. Hernandez *et al.*, (2008), addressed the problem of when benchmark and rating data is unavailable and discussed a method for determining these unknown variables.

Data collection is the first step in determining benchmarks and ratings. Questionnaires were sent to over 500 primary schools in Ireland to answer three basic categories of questions; a) general data, b) construction data and c) services. The general data involved determining school name, the location and pupil numbers. The

construction data was used to determine the U-values of the materials used and technical drawings. Lastly, the services questions were used to establish heating, cooling, ventilation, heating hours, boiler type and efficiency, primary source of fuel, hot water systems and energy consumption. Hernandez *et al.*, (2008), stated that out of the 500 schools approached in the study, only 67 (13.5%) schools replied.

The questionnaire responses provided adequate information on the first two categories of question, but only 46 (67%) (out of the 69 responses) provided sufficient details on the energy consumption of the school. Hernandez *et al.*, (2008), stated that a key part of determining the benchmark is having accurate demand data. As a result of this problem, a new shorter questionnaire was sent out to 500 schools. The shorter questionnaire asked only for annual fuel consumption and total floor space. A further 62 replies were added to the previous 46, resulting in 108 values for energy consumption in schools.

The next stage of determining benchmarks, as described by Hernandez *et al.*, (2008) is analysing the consumption data to find the median. The median value was 96kWh/m²/yr and was used as the building stocks energy benchmark. The ‘current practice’ or current energy consumption benchmark was 65kWh/m²/yr and was found by finding the upper quartile of the results. Hernandez *et al.*, (2008) moved on to discuss how the benchmarks are used to form energy ratings and categorising buildings. First of all Hernandez *et al.*, (2008) defined two different type of ratings; a) calculated energy rating and b) measured energy rating. The calculated rating is based on building drawings and construction details. Hernandez *et al.*, (2008), stated that this can be also called ‘asset energy rating’, when calculated for a built building or ‘design energy rating’ for a building that is still in the design stage. The measured energy rating, as stated by Hernandez *et al.*, (2008) is the measure annual energy consumption of the building, and can be also called ‘operational rating’.

Both ‘operational and asset’ ratings are the same definitions used/stated in Bordass *et al.*, (2004). Hernandez *et al.*, (2008) provided an example to demonstrate how the benchmarks are used to determine school ratings. One school was taken as a sample and information about the school was collected. The EnergyPlus modelling software was used to calculate the ‘asset energy rating’. The program can calculate the energy usage based on the information supplied from the original questionnaires. To determine the school category, Hernandez *et al.*, (2008) adopted a similar method described in “Energy Performance of Buildings” paper. The calculation used three variables; a) EP, which is energy performance, b) Er, which is the energy reference, and

c) ES, which is the building stock reference. The three variables were calculated using the EnergyPlus software and the classification was determined using the table shown in figure 12. The table shows the different tests that establish the school's class.

Using the sample school discussed in Hernandez *et al.*, (2008) the variable values found were as follows; $EP=31\text{kWh/m}^2/\text{yr}$, $Er=18\text{kWh/m}^2/\text{yr}$ and $Es=54\text{kWh/m}^2/\text{yr}$. Hernandez *et al.*, (2008) stated that the example school was given a class C rating, using the table, as shown in Figure 12 as a reference.

Class A	$EP < 0.5R_r$
Class B	$0.5R_r \leq EP < R_r$
Class C	$R_r \leq EP < 0.5(R_r + R_s)$
Class D	$0.5(R_r + R_s) \leq EP < R_s$
Class E	$R_s \leq EP < 1.25R_s$
Class F	$1.25R_s \leq EP < 1.5R_s$
Class G	$1.5R_s \leq EP$

Figure 12 - Benchmark Criteria Table Hernandez *et al.*, (2008)

Hernandez *et al.*, (2008) proceeded to calculate the operational rating of the example school. This involved taking the total annual fuel consumption, 8760L of oil, and the floor space, 1760m^2 , to calculate the energy performance of $53\text{kWh/m}^2/\text{yr}$. Using the data found during the analysis stage, Hernandez *et al.*, (2008) used the following values; a) $Es=96\text{kWh/m}^2/\text{yr}$ and b) $Er=65\text{kWh/m}^2/\text{yr}$. Using Figure 12 as a reference, the example school can be classed as 'B', based on the operational rating. It can be seen that there is a classification difference between the calculated and actual energy consumptions of the building. This highlights the problem of using modelling to determine energy benchmarks.

There are several issues with the work undertaken by Hernandez *et al.*, (2008). The first is that not enough information is given about how the table shown in Figure 12 was constructed. It is unclear what variables influence the classes or the reasoning behind the class tests. The second issue is that there was no reason given for why EnergyPlus software was used, and not any other energy simulation tools. Lastly, there was no reasoning behind using the results median as the building stock performance benchmark, not the results upper quartile as the "current practice". However Hernandez *et al.*, (2008) discusses the benchmarking process well enough to give a basic understanding on how to construct benchmark tables.

The benchmarks and benchmarking methodology outlined in Stoy *et al.*, (2006) and National Statistics, (2004) were based on a statistical analysis of a large energy

database. Unlike the methodology discussed in Hernandez *et al.*, (2008), and Chung *et al.*, (2006), the methodology does not involve linear regression models, or a simplistic statistic approach. A large database of various types of buildings in Switzerland was constructed. The database was created using property surveys and included 109 offices.

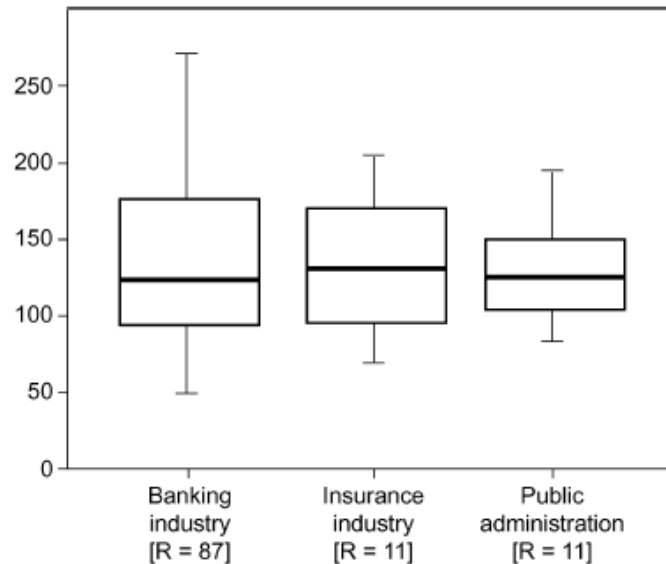


Figure 13 - Energy Consumption in Different Sectors Stoy *et al.*, (2006)

One of the first stages of the analysis was to separate the data or categorise the various buildings into their correct grouping. The three main groupings used by Stoy *et al.*, (2006) were; banking, insurance and public administration. Figure 13 highlights the initial analysis of the database showing results for each of the studied sectors. For each of the sectors, the maximum, minimum, median and the lower and upper quartiles are presented. The advantage of including the maximum and minimum values in the database, is that it indicates how varied the database can be. It can be seen in Figure 13 that the median for all three categories is very similar, ($\sim 125 \text{ kWh/m}^2/\text{yr}$), however the quartiles and maximum/minimum are different. There is considerable difference between the maximum and minimum values of the banking industry and the public administration. The differences will be due to the variation in category size (note that there are 87 banking offices, compared with 11 insurance and 11 public administration buildings).

The median can be used as a typical or an average benchmark, to represent the dataset and ideally the stock. The upper quartile could represent the worst case scenario, or a building that has little energy saving measure in place (or a power intensive building). Conversely, the lower quartile represents a building with relatively low energy consumption, perhaps an example of an energy efficient school.

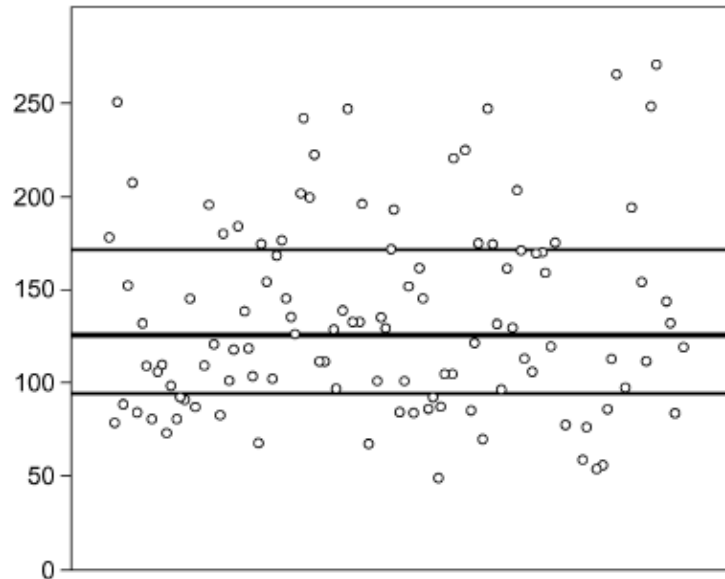


Figure 14 - Energy Consumption and Analysis of Building Dataset Stoy *et al.*, (2006)

If the full dataset discussed in Stoy *et al.*, (2006) is studied at a non-categorised level (all buildings together) and analysed using a similar methodology as shown in Figure 13, the results differ. The results from investigating the entire data set are presented in Figure 14. The total energy consumption per floor area is on the ‘Y’ axis and each studied building is on the ‘X’ axis. The thick horizontal line represents the median and the lines above and below it represents the upper and lower quartiles. An interesting observation is that the median is the same ($\sim 125 \text{ kWh/m}^2/\text{yr}$) in this analysis as with that found in the previous analysis (Figure 13). This not a surprising outcome as the same data set is being used as before, and there was little variation in the calculated median between the categories. One difference between each of the results is the upper and lower quartiles. The quartiles appear to be more related to those of the Banking industry offices. This again could be related to the large proportion of bank offices in the dataset.

A large study that resembles the benchmarking methodology used in Stoy *et al.*, (2006) was used in National Statistics, (2004). Unlike the previously discussed studies, that involved analysing relatively small databases, this report investigated every school in England (both primary and secondary). This created a large database for the two types of school.

The methodology outlined in Stoy *et al.*, (2006) involved taking the median, upper and lower quartiles, and the maximum. The National Statistics, (2004) involved creating benchmark tables with five percentiles; 10th, 25th, 50th, 75th and 90th. This creates a larger selection in benchmark results for the two categories of school.

2.6.2 Current Benchmarks

This section details several available benchmarks for both offices and schools. Each table highlights different levels of energy performance benchmarks for different buildings, as well as the associated study. Lastly this section investigates the problems with using benchmarks and the factors that influence energy usage hence the performance benchmarks.

2.6.2.1 Office Benchmarks

Table 1 - Office Energy Benchmarks

Source	Good (kWh/m ² /yr)		Typical(kWh/m ² /yr)	
	Electricity	Fossil	Electricity	Fossil
Carbontrust, (2003)(1)	33	79	54	151
Carbontrust, (2003)(2)	54	79	85	151
Carbontrust, (2003)(3)	128	97	226	178
Carbontrust, (2003)(4)	234	114	358	210
Stevens, (1998)	36	47	356	180
Stoy <i>et al.</i> , (2006)	94	-	125	-

The office benchmarks found from previous studies are presented in Table 1. The table has both ‘Good’ and ‘Typical’ benchmarks, representing the lower percentile (or lower quartile) and the average/median respectively. The table is also broken down into different energy usage, either electricity or fossil fuel. Within the studies, the Energy Consumption Guide – Energy Use in Offices (Carbontrust, (2003)) has four different sets of energy benchmarks; with vary ranges of benchmark figures, based on four types of office buildings.

Table 1 highlights the varied office energy benchmarks available from the different studies. The ‘Good’ electricity ranges from 33-234kWh/m²/yr, and fossil from 47-114kW/m²/yr. Similarly, the ‘Typical’ values range from 54-358kWh/m²/yr for electricity and 151-210kWhr/m²/yr for fossil fuels. The wide range of energy benchmarks, reflect the different studies, and the different datasets analysed. This variation can make it difficult for users to select an appropriate benchmark.

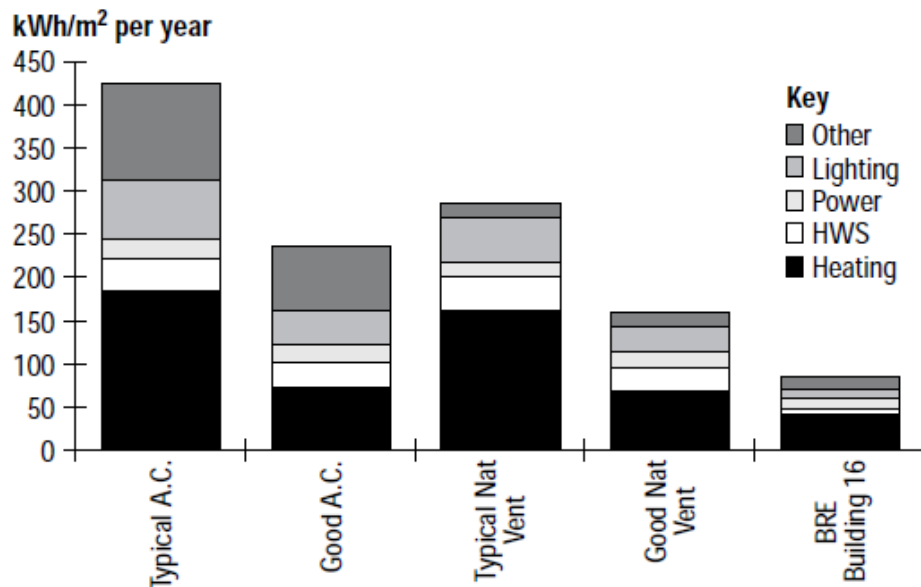


Figure 15 - Benchmarks Stevens, (1998)

A study into building a lower energy use office Stevens, (1998) produced the chart shown in Figure 15. This chart shows the energy benchmarks for five different types of building. This Figure provides further detail, by disaggregating the benchmark value in different energy end use categories, such as lighting, power and hot water system. Figure 15 also provides an insight into the differences in benchmarks between the types of building (i.e. air conditioned (AC) and naturally ventilated (NV)). In addition the figure also incorporates a ‘Good’ and ‘Typical’ rating, similar to the one used in Table 1. The main energy end uses which appear to change in the different types of offices are the ‘Heating’ and ‘Other’ sectors. These sectors must be influenced by certain variables that change between building type. These dependencies are discussed further in Section 2.6.4

2.6.2.2 School Benchmarks

When comparing a studied building with known energy performance benchmarks, it is important that the correct performance benchmark is selected. The correct selection can be difficult, as there are several studies and building types, hence various energy performance benchmarks. Similarly, if another type of non-domestic building is being studied, the appropriate benchmarks must be used.

For schools, the benchmark data provided in Table 1 is not appropriate. Another issue is that within the school sector there are ideally two distinct categories, primary and secondary. It would not be appropriate to compare a primary school with a high school benchmark, similarly as comparing a small office with a large AC office benchmark. The distinction between primary and secondary schools is based on the

assumption that there is different equipment lists and equipment usage (see Section 2.5.2). It is important then to create two separate benchmark tables for primary schools and secondary schools.

Table 2 highlights several energy performance benchmarks and their associated study. One difference in the benchmarks shown in Table 1 and Table 2 is that there is an additional benchmark rating, creating ‘Good’, ‘Typical’ and ‘Bad’ ratings within benchmarks (unlike the ‘Good’ and ‘Typical’ ratings for the office benchmarks). This provides an improved rating system for comparing a studied school.

Table 2 - Primary School Energy Benchmarks

	<i>Good (kWh/m²/yr)</i>		<i>Typical(kWh/m²/yr)</i>		<i>Bad(kWh/m²/yr)</i>	
	Electricity	Fossil	Electricity	Fossil	Electricity	Fossil
Carbontrust, (1999)	25	110	34	157	47	209
Hernandez <i>et al.</i> , (2008)	-	-	65	110	96	157
National Statistics, (2004)	8	50	37	158	69	271

The ‘Good’ electricity benchmarks range from 8-25kWh/m²/yr and 50-110kWh/m²/yr for fossil fuels. This is a wide variation, and could be due to sample size, or alternatively how the data was sampled (quartiles or percentiles). The ‘Typical’ benchmarks appear to have a smaller gap between them, and the figures from school Carbontrust, (1999) and National Statistics, (2004) appear to be almost identical. This could be due to a similar sized dataset. Similarly, the ‘Bad’ benchmarks for Carbontrust, (1999) and National Statistics, (2004) appear to be fairly similar, with 22kWh/m²/yr and 62kWh/m²/yr difference for electricity and fossil fuel respectively.

Table 2 highlights that even within a sub-group of a non-domestic sector there can be variation within the energy performance benchmarks.

Table 3 - Secondary School Energy Benchmarks

	<i>Good (kWh/m²/yr)</i>		<i>Typical(kWh/m²/yr)</i>		<i>Bad(kWh/m²/yr)</i>	
	Electricity	Fossil	Electricity	Fossil	Electricity	Fossil
Carbontrust, (1999)	26	117	36	160	45	207
Carbontrust, (1999)with pool	29	142	36	187	41	233
National Statistics, (2004)	20	45	39	155	62	270
Dimoudi <i>et al.</i> , (2009)	10	32	20	57	-	-
Santamouris <i>et al.</i> , (2007)	-	-	27	68	-	-

Table 3 demonstrates several energy performance benchmarks for secondary schools, presented in the same format as the primary school benchmarks, shown in Table 2. One important difference between the primary and secondary schools is that a further sub-category is included. The second row of benchmarks represents a secondary school with a swimming pool. As discussed in (breakdown of energy in schools), there is a noticeable difference in energy consumption (as well as how the energy is consumed) between a school that has a swimming pool, and one that does not. The Carbontrust, (1999) makes this distinction between the two types of secondary schools.

The ‘Good’ energy benchmarks range from 10-29kWh/m²/yr for electricity and 32-117kWh/m²/yr for fossil fuels. The ‘Typical’ benchmarks range from 20-39kWh/m²/yr and 57-187kWh/m²/yr for electricity and fossil fuel respectively. Lastly the ‘Bad’ energy benchmarks range from 41-62kWh/m²/yr for electricity and 207-277kWh/m²/yr for fossil fuels.

One observation of Table 3 is the differences between the benchmarks given by Carbontrust, (1999), for the school with a swimming pool and one without. For the ‘Good’ rating there is a 3kWh/m²/yr difference in the electricity consumption and 25kWh/m²/yr for the fossil fuel consumption. This would be expected as extra gas is used to heat the pool water and additional electricity is required to pump the heated water from the boilers to the pool. The ‘Typical’ benchmarks have no difference in the electricity usage and a increase of 27kWh/m²/yr for the fossil usage. Lastly the ‘Bad’ benchmarks have a decrease of 4kWh/m²/yr for electricity usage and an increase of 26kWh/m²/yr for the fossil fuels (in relation to the school with the swimming pool).

The ‘Bad’ rating, there is a reduction in electricity consumption for the school with the swimming pool, compared with a school without a pool. This anomaly could be due to the range of the school data set, and how that dataset was analysed. The results also demonstrated that there is around a 26kWh/m²/yr increase in fossil fuel consumption for a school with a swimming pool. The marginal difference in electricity usage could be down to the individual schools, and how water is pumped to the pool.

2.6.3 *Benchmark Issues*

Table 1, Table 2, and Table 3 highlight that there has been several different benchmarks produced from a variety of studies. As discussed at the start of this section, benchmarks have several advantages (quick reference, insight into building efficiency). However, there are one or two issues with energy performance benchmarks. One issue with these forms of benchmark figures is that they only give estimated annual energy consumption for a certain generalised category of building. This gives little insight into the daily, weekly or even seasonal variations. There are several factors that can influence the energy consumption of a building. The surrounding climate will have an impact on an building’s energy consumption, with buildings in a tropical environment having different energy requirements than a building in a cooler climate. Evidence of this climate influence can be seen when investigating different benchmarks. In Hong Kong, the electricity benchmark for an office is 270kWh/m²/yr (Lam *et al.*, (2008)), whereas an office in a Nordic country can have an electricity benchmark of 144kWh/m²/yr (Junnila, (2007)). This can also be seen in schools, with a Greek school consuming 95kWh/m²/yr (Dimoudi *et al.*, (2009)) and 65kWh/m²/yr for an Irish school (Hernandez *et al.*, (2008)). Additionally, how the building is used and the number of occupants can also influence building energy consumption, though it is very difficult to understand how energy is used without breaking down that energy use by time of day. This shows the importance of collecting data at a suitable level of temporal precision/resolution.

2.6.4 *Dependencies*

In section 2.2.4, it was discussed that a potential issue with benchmarks is that they can vary between different published studies. The different studies were carried out in different countries, introducing the concept that energy consumption can be influenced by outside factors (i.e. environment/climate). This section discusses the various influencing factors or dependencies that can affect energy use.

The technology to gather demand data, whether it is electricity or gas, is only one part of understanding energy use in buildings. The gathered demand data provides clues on how much energy is used in a day, week, month or year, and can provide load profiles. What is needed, however, is an insight into why the building consumes a certain amount of energy. This section investigates the main factors that can influence energy usage in a non-domestic building.

Work by Lam *et al.*, (2008) provided the first insight into what factors, if any, affect energy consumption in non-domestic buildings. Lam *et al.*, (2008) investigated how building energy efficiency varied in different climates, focusing on China. The aim of the investigation was to determine if there were any seasonal differences between the energy consumed by HVAC systems and the different climate zones. Lam *et al.*, (2008) believed that up to 65% of energy usage in the non-domestic sector in China was due to HVAC systems. The comparisons would be simulated using an energy simulation tool/package. Five cities in China were selected, each having a different climate. These were as follows; a) Harbin, severe cold, b) Beijing, Cold, c) Shanghai, hot summer and cold winter, d) Kunming, mild, and lastly e) Hong Kong, hot summer and warm winter. An advantage of studying China, suggested by Lam *et al.*, (2008) is that it has varying climates in each province.

The first stage of the investigation was looking at the weather data available for each of the cities. Lam *et al.*, (2008) stated that “all energy simulation computer programs require weather data input to drive the thermal models within the simulation tool”. A template building was developed with set parameters that were used for each of the cities. These parameters included floor space, indoor thermal comforts for summer and winter, window to wall ratio and lighting load intensity (W/m²). Additionally operating hours and number of working days in a week were also included. Lam *et al.*, (2008), pointed out that although a generic building was used, certain U-values and shading coefficients were modified for the different regions. This was justified by stating that the buildings in each climate region would be built to suit that certain climate. Generally buildings in a colder region would have better insulation, especially for the winter months, whereas in a hotter climate, wall insulation is not considered important.

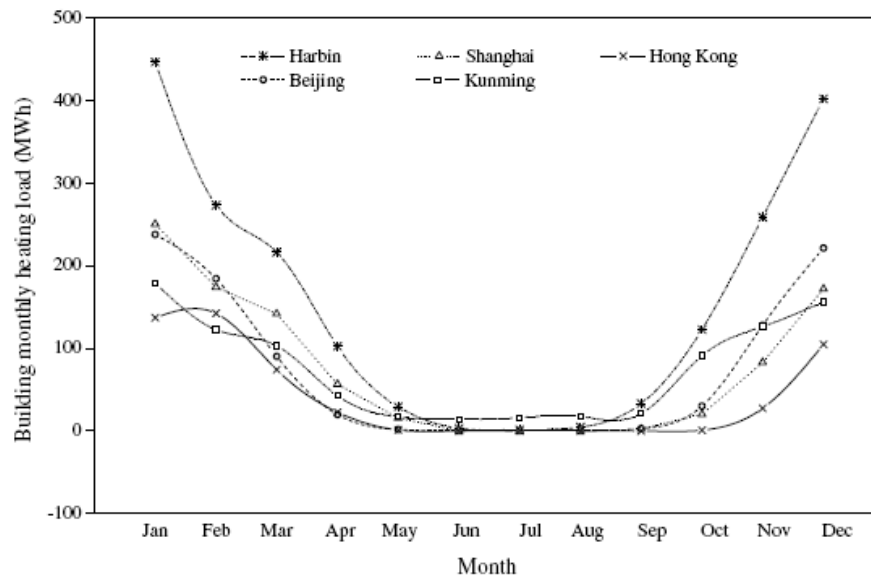


Figure 16 - Annual Heating energy Consumption Lam *et al.*, (2008)

The weather data and the generic building, adjusted for the different climates, were used in the energy simulation tool to provide monthly and annual energy consumption values. Figure 16 demonstrates the monthly energy consumption associated with heating for each of the climate buildings. It can be seen that each building uses a large amount of energy during the winter months that gradually lowers towards the summer months. It can be seen that all five buildings use a similar amount of energy during the summer months. This could be due to neither building using any heating during these months.

The main differences are between the winter consumption values. Harbin appears to consume the most energy during the winter (over 450MWh) followed by Beijing (over 250MWh). It could be assumed that Harbin, being the severe cold climate city, would use more energy for heating to compensate for the colder outside temperature. The boilers would have to use more fuel to maintain the preset thermal comfort of the building if the outside temperature was low. Equally so, those buildings in the warmer climates, Kunming and Hong Kong, have a warmer ambient temperature than the cold climates. The boilers would have to work less, to maintain the desired thermal comfort, and hence consume less fuel than a cooler climate.

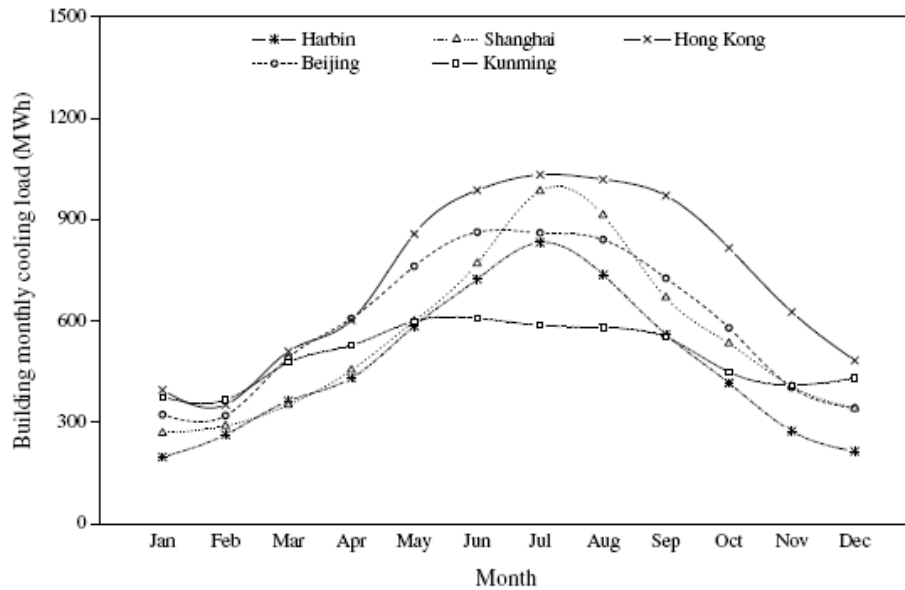


Figure 17 - Annual Cooling Energy Consumption Lam *et al.*, (2008)

The monthly energy consumption associated with cooling (air conditioning/mechanical ventilation) is shown in Figure 17. The figure demonstrates that the cities in the hotter climates (hot summer) consume a larger amount of energy than those in the cooler climates. An interesting point made by Lam *et al.*, (2008) was that although the hotter climate city peaked at 1033MWh (in July), Harbin had a peak that was only 20% smaller. It would have been assumed that the colder climate would have had a much lower cooling load, hence lower consumption. Lam *et al.*, (2008) argued that the Harbin building had different thermal properties and different shading coefficients, resulting in a possible increase in solar gain. The increased solar gain would result in more energy being consumed by the HVAC system to compensate the increased internal temperature.

From the results gained by Lam *et al.*, (2008) it is possible to conclude that there are several outside factors that affect the energy consumption of a building. The first factor that seemed to effect consumption was the weather, though mainly the outside temperature. It can be observed in figure (HVAC system) that those buildings in the hotter climate consumed more energy due to an increase of loading on the air conditioning systems. Equally so, those buildings in the cooler climates, tended to consume more energy through boiler use, than those in the hotter climates. The heat gains, mainly solar, are important to consider in any building because any heat gain will effectively increase the indoor temperature. This in turn will cause an increase load on any cooling systems, hence increase the energy consumption associated with those systems.

It is also important to consider the window sizes, materials and thickness to better understand solar heat gain. Additionally, the insulation of a building is important. Part of the investigation carried out by Lam *et al.*, (2008) was modelling buildings from different climates that each had different insulation materials. These insulation materials, as discussed by Lam *et al.*, (2008) were adjusted to suit local building materials and building techniques. It would be helpful to have an insight into the buildings insulation, relative to the environment it is in. Too much insulation in a hot climate could result in high cooling loads. Similarly too little insulation in a cold climate could impact on the heating loads. It is worth while considering these points when studying a building.

Further clues into what factors effect energy consumption in buildings was given by Chung *et al.*, (2006). As discussed in a previous section, Chung *et al.*, (2006) investigated how to benchmark the energy efficiency of commercial buildings. At the end of the investigation, a linear regression equation was formed which was based on a variety of factors. The first factors are based on the building and include the age, floor size, operational schedule and equipment type. Another contributing factor, as mentioned by Chung *et al.*, (2006) was the outside temperature. This variable, unlike Lam *et al.*, (2008) was calculated in degree days, as opposed to just standard degrees. Additionally, Chung *et al.*, (2006) does not mention any other weather variables that might influence the energy consumption.

The benchmarking technique discussed in Stoy *et al.*, (2006) and outlined in section 2.6 investigated the drivers of electricity consumption. Similarly with Chung *et al.*, (2006) and Lam *et al.*, (2008), Stoy *et al.*, (2006) studied the main influencing factors of energy consumption in an office building. Instead of focusing on outside factors such as weather/temperature, Stoy *et al.*, (2006), focused on actual building properties. These properties included; share of ventilated areas (x_1), share of air conditioned spaces (x_2), number of lift stops(x_3), share of recreational areas (x_4) and data processing centre (x_5). A regression analysis provided the following equation;

Equation 1 Regression Analysis (Stoy *et al.*, (2006))

$$y = 4.86 + 35.86x_1 + 63.93x_2 + 2730.64x_3 - 91.57x_4 + 74.35x_5$$

Where Y = total electricity consumption in kWh/m²

It was found that although the previously stated factors were found to influence the energy consumption of an office building, only two factors were main driving

forces. These were identified as the share of ventilated spaces and the share of air conditioned spaces.

One issue with the energy driving factors, is that they may not all apply to offices, such as the number of lift stops. Additionally, the research was carried out on Swiss office buildings, where air conditioned offices are very common (according to the dataset used in Stoy *et al.*, (2006)). The UK's non-domestic building stock may not use the same level of air conditioning as the rest of Europe. This is an important factor to consider when determining energy driving forces for the UK office building stock.

The work undertaken by both Lam *et al.*, (2008), Stoy *et al.*, (2006), and Chung *et al.*, (2006) provided a basic understanding on what can affect the energy consumption of a building. This insight helped create an idea on what is important to monitor in a building, other than electricity and gas usage. It can be understood that the important factors that should be monitored are; a) floor size, b) insulation (type and thickness), c) outside weather, d) solar energy, e) building type and f) equipment lists. By monitoring these variables, a better understanding of how energy is used in a building should be achieved.

2.7 Non-Intrusive Load Monitoring (NILM)

Load monitoring can be broken into several key areas. The first area is energy or load monitoring and the technology and methodology associated with it. The second is investigating what load profiles are and why understanding them is beneficial. The last section deals with the benefits and problems associated with implementing load monitoring and appliance monitoring.

2.7.1.1 Load/Energy Monitoring

Load monitoring is recording the energy consumed by a building over a given or preset time. Stuben *et al.*, (1997) stated that load monitoring systems can provide information on voltage, current, waveforms, power and breaker status. For accurate energy monitoring the power needs to be known for a given time. The breaker status as mentioned by Stuben *et al.*, (1997) most likely refers to large industrial or sub-station monitoring, not domestic, or for this thesis, office/school monitoring. According to Farinaccio *et al.*, (1999) there are five operational steps in Non-Intrusive Load Monitoring (NILM) ; a) current and voltage measuring at set intervals, b) detection of On /Off events, c) clustering of comparable events, d) matching events over time, and

finally d) equipment recognition. It can be assumed that the first two stages of NILM are for data gathering and the other three are for data analysis.

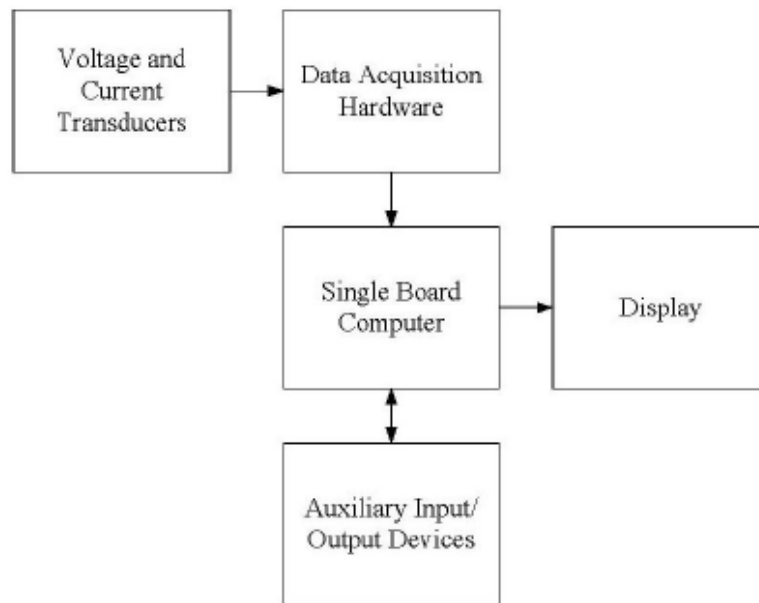


Figure 18 - Diagram Showing Basic Load monitoring layout Shenavar *et al.*, (2007)

A basic overview on how load monitoring equipment works is highlighted in Shenavar *et al.*, (2007) and is shown in Figure 18. The figure shows the main components of a successful energy monitoring set up. The main input is the voltage/current transformers, detecting the electricity flow (or by using optic sensors on the gas or electricity meter). These signal inputs are fed into a data processor (computer), and the data can either be displayed or outputted to a data logger (or saved to an internal data logger).

Norford *et al.*, (1996), suggests that load monitoring can be useful in providing knowledge of energy use in individual buildings. There are several load monitoring criteria stipulated in Norford *et al.*, (1996). The NILM system should be; a) easy to install, b) automatically detect loads and subsequently identify them and finally c) the system should be able to be used for ‘on site’ analysis. On-site analysis is being able to access and process the monitored data without removing or disconnecting the monitoring equipment. The main issue with these criteria is that it would be very difficult to automatically identify an individual appliance from a total energy profile. One issue raised in Norford *et al.*, (1996) is the monitoring of variable loads, such as air conditioning systems and mechanical ventilation.

Variable loads, conversely, are more difficult to detect because the corresponding on/off signature may change depending on length of operation, time of

year and how the load is being used. Another problem with NILM as mentioned by both Norford *et al.*, (1996) and Shenavar *et al.*, (2007) is confusion in appliance identification. When several loads are turned on at the same time, there can be errors or confusion in the NILM identification process. An example provided by Shenavar *et al.*, (2007) reinforces this point. A 100W light bulb may produce a very similar, if not identical profile as five 20W light bulbs. It should be noted that the work carried out by Norford *et al.*, (1996) aimed at monitoring residential or domestic sector. Commercial buildings can produce very smooth electrical loads compared with domestic energy use that is usually characterised by ‘spikey’ data. This could result in small changes in use of energy in the non-domestic sector, not being noticed by a load monitoring system.

Both Hart, (1992), and Akbar *et al.*, (2007) investigate energy usage of buildings by using Non-intrusive Appliance Load Monitoring (NIALM or NALM). NALM is almost the same concept as NILM, in that energy consumption is recorded. The main difference between the two concepts is that in NALM, the energy consumption of individual appliances determined using total energy demand. Hart, (1992) argues that NALM can be used to determine individual appliance demands provided detailed total load and voltages are known. Similarly, Akbar *et al.*, (2007) states that NIALM is a modern technique for working out appliance demand profiles from a single monitoring point. Both Akbar *et al.*, (2007) and Hart, (1992) agree that each appliance has its own unique energy demand signature. An advantage of using NIALM, as discussed in Hart, (1992) over traditional monitoring techniques is the effectiveness of non-intrusive monitoring. Previous monitoring techniques have involved inserting power analysers into equipment, which can be either intrusive or inconvenient. NIALM can be placed in existing power systems with no interference to the customer’s equipment or power supply.

Hart, (1992) discussed NALM further by introducing two variations of this monitoring concept. The first is manual setup NALM, (or MS-NALM), is a semi intrusive monitoring system. The system uses an intrusive approach to monitor individual appliance signatures that are manually switched on and off. These signatures are then subsequently saved and labelled for later use. Hart, (1989) and Hart, (1992) argued that although this system is intrusive, it is a process that happens only once, and can be done off site. The second system is automatic setup NALM (or AS-NALM) that uses pre-stored signatures to automatically recognise appliances from their individual signatures. An important difference between manual and automatic setup is that the automatic system is completely non-intrusive. Hart, (1992) stated that “*MS-NALM is a*

stepping stone in the development of AS-NALM, but AS-NALM will dominate in most applications”.

There can be several financial and power related benefits of using an energy monitoring device, whether it is a domestic or non-domestic application Stuben *et al.*, (1997). The first is avoiding investment. Large companies can use monitoring equipment to determine a piece of equipments condition or whether improvements can be made. NILM can be used to determine how energy is being consumed in an appliance. Stuben *et al.*, (1997) gives an example of a chemical processing plant that had several problems with overloading in one of the process feeders. It was not known what was causing the overloads, and rather than replace the feeders, NILM equipment was introduced and the problem identified. The company saved \$1 million by not investing in new feeders.

The second advantage is justifying minimum investment. Modernisation of buildings, mainly industrial plants generally will require a review of the current power supply. If the new modern retrofit will have a greater demand than the original demand, the power suppliers may need to upgrade. The power upgrade could consist of new transformers, switchgear and new lines, all of which are expensive. If it could be determined by a load study that the new demand could be kept within the limits, then an upgraded power supply may not be needed. Another practical example from Stuben *et al.*, (1997) described a chemical plant that was being refitted. A load study determined that the demand would fall within the limits of two new sub-stations, rather than the original proposed three new sub-stations. The concept of minimum investment appears to be ideal in theory, but it also appears to be a short term ideology. If the new factory meets the new limits for the first year, but then changes a process that in turn results in an increased power demand or maximum peak demand. This could cause major issues for both the customer and the power company, if power demand is not correctly regulated.

The third benefit in energy monitoring as discussed by Stuben *et al.*, (1997) is improving cost allocation. Large offices/buildings and industrial plants have several key areas or process that consume different amounts of power. These separate areas can be individually monitored to give a breakdown or understanding of where and how much power is being used. If a company incorrectly invests energy saving equipment in a non-key area then no real impact in saving energy may occur. Additionally the new investment may be seen as a waste of money. Load monitoring can highlight where the

most energy intense areas are and subsequently change the cost allocations for both power and energy saving equipment.

Using monitoring systems can determine what a building peak looks like and possible solutions for reducing it. A final example is given in Stuben *et al.*, (1997) of a chemical company that had large demand bills because of motor demand peaking and motor start ups. The company used energy monitoring to determine their demand. By installing automatic motor shutdown systems and deferring when the motors start up, the company now saves \$150,000 a year. Although the discussed benefits are aimed at more industrial applications, they do highlight that energy monitoring can provide several advantages to an office or company such as energy and financial savings.

2.7.2 Load Profiles and Profiling

Load profiles are essentially visual representations of energy demand over time. Load profiles are defined as the pattern of electricity use of customers in a supply segment (UK Energy Research Centre, (2011)), where segment means the customer sector. Load profiles demonstrate the relationship between consumer behaviour during the day and the resulting energy consumption. UK Energy Research Centre, (2011) defines load profiles as the ‘shape’ of electricity usage across the day or even year. Generally a load profile is the outcome of load or energy monitoring exercise. According to Wright *et al.*, (2007) load profiling was initially associated with the electricity market, but because of its use as a management tool, has spread to other utilities including gas and water. The resolution of a load profile is extremely important. For domestic load profiles a time factor, or time interval, of one minute is ideal, whereas for non-domestic the recognised time resolution is thirty minutes, as discussed by Wright *et al.*, (2007) and Zakaria *et al.*, (2002). The reason for the difference is appliance or equipment activity. In a dwelling, lights and appliances will be regularly turned on and off depending on the consumer’s behaviour. To obtain and record the on/off characteristics of energy use, a fine resolution is required to ensure events are not missed. Non-domestic buildings, e.g. offices, usually have large quantities of lights, computers and photocopiers. One or two appliances switched on or off will make little impact on a large office load profile. Subsequently, fine recording resolution will provide little additional information on a non-domestic building, hence a longer sampling period can be used.

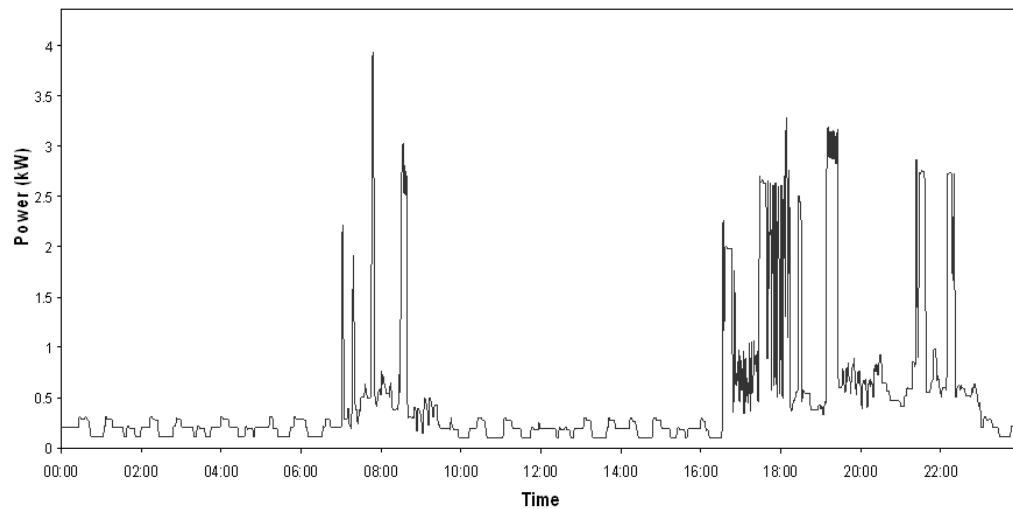


Figure 19 - Example Domestic Electricity Load Profile, Kilpatrick *et al.*, (2011)

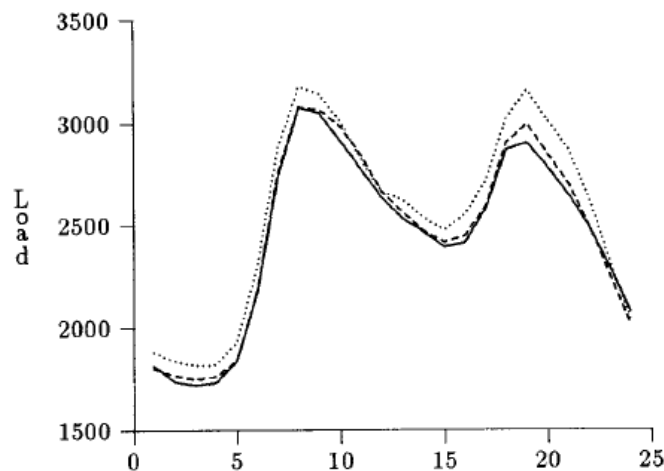


Figure 20 - Example of Non-Domestic Electricity Load Profile, Park *et al.*, (1991)

Figure 19 and Figure 20 demonstrate the differences between a typical domestic profile and a typical non-domestic electricity demand profile. Figure 19 highlights the large spikes that occur throughout the day as the result of electric showers, kettles and dishwashers. If the time resolution was adjusted to half hourly, a large proportion of this detail would disappear. Figure 20 demonstrates a fairly smooth demand profile, with two clear peaks in electricity load. It is assumed that the X axis represents a 24 hour time frame, although this is not stated in Park *et al.*, (1991). If the time resolution was increased from half hourly to minutely, there would be little change in profile shape.

Investigations carried out by Zakaria *et al.*, (2002) and Nizar *et al.*, (2006) gave insight into the need for load profiles and load profiling. The majority of the commercial uses of load profiles are focused on power companies. It is stated in Zakaria *et al.*, (2002) that profiling can help power companies with power forecasting, system management and demand side management. Load profiles can also help power companies calculate the different pricing periods for consumer electricity demand.

Nizar *et al.*, (2006) discusses that within the initial customer classifications of domestic and non-domestic, further classifications can be found.

Power companies can use load profiles to establish new services and tariffs to suit certain customers. The main problems with using load profiles to determine customer behaviour is that first load profile data has to be collected. As discussed in the previous subsection, load monitoring equipment is needed to gather demand data. As mentioned in Zakaria *et al.*, (2002) the ability to monitor several millions of customers is neither cost effective nor feasible. Another factor that limits using individual load profiles for every customer is time. It would take vast amounts of time to analyse and process the load profile data. To overcome these issues, a new concept of load profiling is introduced. Load profiling, as described as Zakaria *et al.*, (2002) is using historical or current load data to predict or estimate the ‘shapes’ of electricity use for customers. Power companies will generally use load profiling and take the standard monthly meter checks to ensure the estimated profiles match the customer’s electricity usage.

According to Zakaria *et al.*, (2002), there are two main processes of load profiling. The first stage is to estimate an average load profile to represent a classification of customer. The second stage is to then apply the determined average profile to each customer in that classification. Load profiling is based on customer energy consumption behaviour. Zakaria *et al.*, (2002) believed that there were two different types of modelling that can be used to determine the average load profile. These methods are; area model and category model. The area model is when customers are grouped together by a geographical zone and network. The category model is where customers are categorised according to their energy usage. Customers in each category have very similar energy demand hence can be represented by a generic load profile. According to Zakaria *et al.*, (2002) the category model is more popular and accurate in estimating electricity usage. This accuracy is purely dependent on taking extensive measurements to determine the generic profile.

Load profiling however, can suffer from sampling error, modelling imprecision and profile drift (Zakaria *et al.*, (2002)). Sampling error arises when a model, even a well designed model, may produce results that match every load profile within a category. This error is mainly a result of taking a narrow range of samples. Modelling imprecision is where the statistical relationships between the demand and other variables are incorrect. Lastly the profile drift is when several profiles that may have different time intervals are added together for averaging. The main problem with load profiling is that it is estimation based. As with any model, the output will only be as

accurate as the input data. Although meter readings are taken from customers, the sampled customers may not represent the rest of the category.

2.7.3 Examples of Load Profiles and Profiling

There have been several investigations into electricity consumption and load profiles. Wright *et al.*, (2007) focused on analysing range energy data for a wide range of non-domestic buildings. The database consisted of 149 buildings including offices, libraries and schools. The main focus of the investigation was to determine average demand profiles for each type of building, and to determine any ‘building failures’. The failures are defined as events that can be linked to wasteful consumption. The four main building failures are stated as; heating/cooling out-with the season, unoccupied heating/cooling, baseloads and lastly continuous excessive consumption. Each of these problems can be identified by analysing the energy demand data (electricity, gas and water usage).

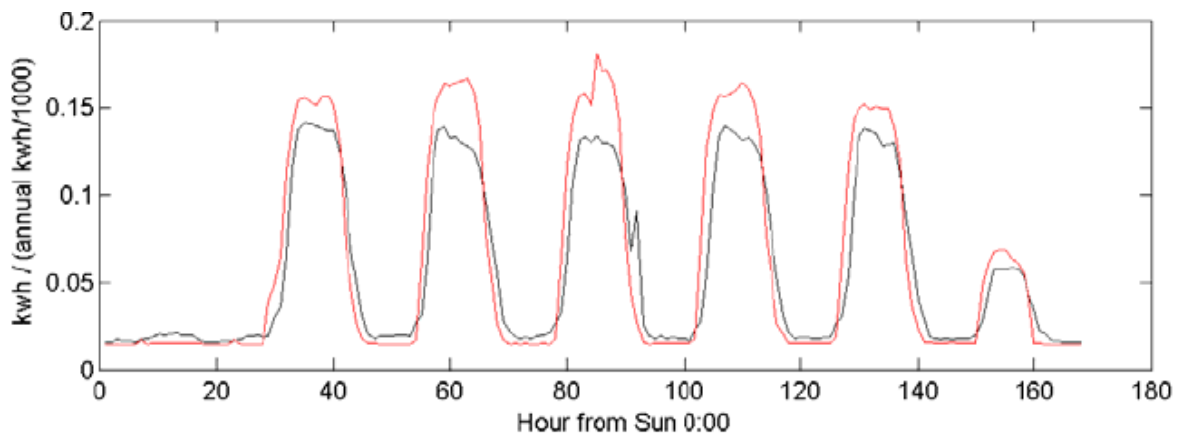


Figure 21 - Office Block Electricity Consumption, Wright *et al.*, (2007)

Figure 21 demonstrates the electricity demand for one of the sampled offices. The profile represents a weekly demand for both the summer season, shown by the red profile, and a black profile for the winter season. It can be seen that the peak demand, as well as total energy consumption, is different between the two seasons. The peak demand of the summer is greater than winter, however the profile shapes appear to be similar. The baseloads also appear to be the same (with marginal variation). The building was identified to have a high baseload, and fell into the baseload building failure. One observation is that, generally buildings should consume more electricity in winter (due to increased lighting and heating pump use), but instead this example building has higher summer demand. This would indicate that the building is air conditioned, hence the extra summer load.

The next stage of the investigation was to analyse the buildings together by type. To carry out this exercise, the data was normalised for fairer comparison. As discussed

in the previous sections, generally the normalisation involves dividing the energy data with the floor area, removing the size factor when comparing data. Wright *et al.*, (2007) used another normalisation technique. The weekly profiles were normalised by the building's total annual energy consumption, providing “equal weight to the shape of the profile” Wright *et al.*, (2007).

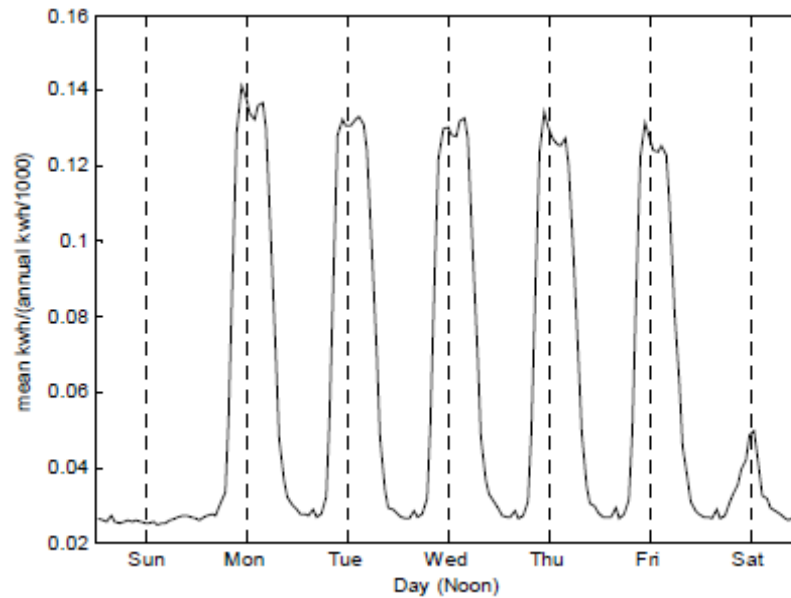


Figure 22 - Typical Office Weekly Electricity Demand, Wright *et al.*, (2007)

Figure 22 demonstrates the weekly electricity demand for a typical office. This was created by averaging the profiles from all the offices within the database (seven for this example). Although not normalised by floor area, the buildings were separated into size classification. Figure 22 represents the average profile for an office over 1000m². It can be seen in the figure that the Monday to Friday profile shapes are almost identical. It can also be seen that there is no active electricity demand on Sunday, but there is marginal electricity usage on Saturday. One disadvantage of the profile shown in Figure 22 is that any possible seasonal variation, as highlighted in Figure 21, is averaged out.

One key output to this investigation is the gas demand profiles. There appears to be little investigation carried out on trends in thermal (or gas) demand, and profile shapes. As well as the electricity data being analysed in Wright *et al.*, (2007) the gas usage for each building was processed. The same analysis technique was applied and the same building failure factors applied. The thermal demand for the same office used in Figure 21, is highlighted in Figure 23.

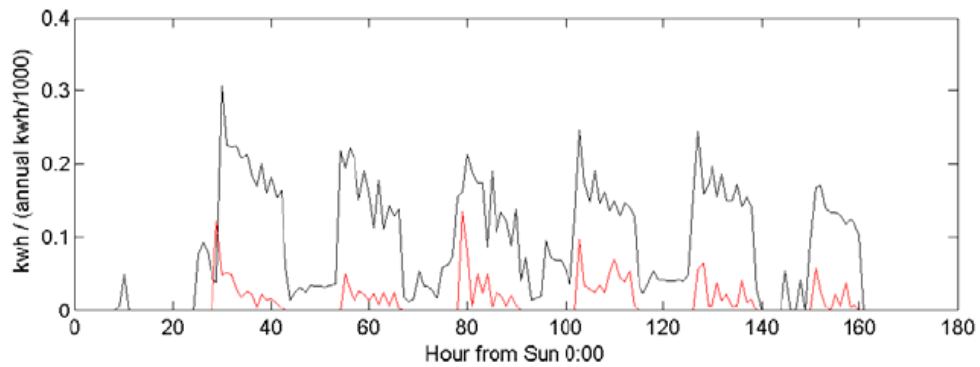


Figure 23 - Thermal Demand of an Office - Wright *et al.*, (2007)

Figure 23 demonstrates that the Monday to Friday gas demand appears to be similar with little variation. The figure also highlights the difference between the summer and winter gas demand. It can be seen that there is a significant drop in consumption during the summer than in the winter. Additionally, there appears to be little weekend energy demand, with only a small peak occurring in winter on the Sunday. This is apparent between the main daily demands and represents a substantial percentage of total weekly demand.

The gas profiles were not averaged to produce typical weekly demand profiles, as with the electricity demand. It was not made clear why this step was not carried out. One possible reason is that the thermal demand is highly dependent on external weather conditions. The data would have to be adjusted by average temperature (or degree day heating) to ensure fair comparison between the buildings. As highlighted in Figure 23, there is a considerable difference between the summer and winter consumptions/demands.

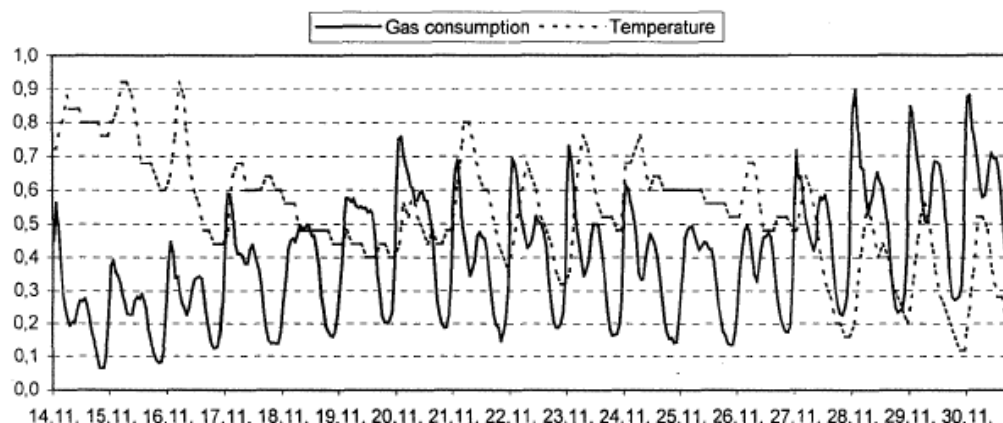


Figure 24 - Gas Consumption Profiles, Peharda *et al.*, (2001)

The influence of temperature on thermal demand and seasonal variation can be seen in Figure 24. The figure shows the gas demand of an office, shown by the solid line, and the outside temperature, shown by the dashed line. When the temperature is

high, the gas demand is low, and vice-versa. When viewed over the two week sample, it can be seen that the temperature slowly falls, whereas the gas consumption rises. It is not known what scale the figure is plotted to, hence difficult to scale the influence of temperature.

2.7.4 NILM Example Methodology

A method for measuring appliance electric demand was discussed in Brown *et al.*, (2008). A key point that is re-emphasised is the need for a non-intrusive monitoring system. Several solutions relating to how to measure total building electricity demand are mentioned in the article. One of these solutions, include using a pulsed output meter that can be used to send pulse data along a special cable to a data logger. Brown *et al.*, (2008) states that this solution sounds ideal, but in reality authorisation is required from the energy supplier's to use the pulse output meter. Simpler solutions to the pulse output meter is using either an optical meter or a magnetic meter. Optical Meter Reading (OMR) exploits newer meters that incorporate a flashing LED. The flashing LED represents a certain amount to energy use. A light sensor, either a light dependant resistor or phototransistor is attached to the meter and aimed at the LED. The sensor detects when there is a pulse and records in a data logger. The consumption can be calculated by recording the number of pulses over a certain time. Magnetic metering works in a similar way, but instead of an LED and light sensor, it uses a magnet and reed switch sensor to detect one revolution of the meter's disk.

Brown *et al.*, (2008) also referred to using current transformers (C.T), as mentioned previously, but stated that C.T's were too inaccurate in detecting low loads. The article suggests that using either the optical or the magnetic meter readers is best suited for total load monitoring; however this technique cannot be applied to individual appliances. This problem is due to optical/magnetic meter readers requiring a meter to gather data from. The majority of individual appliances do not have their own unique meters.

Brown *et al.*, (2008) discussed several options available to monitor appliances, including; a) temperature loggers, b) power meters, c) bench top power meters, d) current clamps, e) magnetic field sensors and f) individual appliance monitoring. Temperature loggers are relatively cheap, but are imprecise and require data processing. Plug in power meters are inserted between the plug of the appliance and the power socket. Brown *et al.*, (2008) pointed out that these sort of meters only provide electrical

consumption at one given time. The plug in meters tend not to have a data logging capability hence cannot produce demand profiles.

Bench top power meters are usually found in laboratories, although bulky compared to the smaller plug in meters, they can provide accurate results. Current clamps, or current transformers rely on manual data gathering and as mentioned above, may not detect small loads. Magnetic field sensors (MFS) can be used to detect and measure any magnetic field surrounding an appliance. More commonly, MFS's are used to monitor motors, transformers and fluorescent lighting ballasts. These sensors would not be useful for monitoring computers or other IT based equipment. Brown *et al.*, (2008) did not describe what 'individual appliance monitoring' in any detail. All that was mentioned was that it can provide extremely accurate results and can provide load patterns. It may be assumed that Brown *et al.*, (2008) is describing single phase electricity monitoring equipment, which includes a data logger, analyser and CTs. These systems are generally quite expensive, used primarily for total load monitoring. To equip every appliance with this technology would be costly. Brown *et al.*, (2008), after discussing the available technology, states that "*it is fundamental that in the majority of cases, an electrical appliance will become warm through normal use*". With this foundation, Brown *et al.*, (2008) believed that by monitoring appliance case temperatures, a low cost demand profiling technique could be developed.

To determine whether the case temperature technique was feasible, an initial experiment was set up. Brown *et al.*, (2008) discussed that a small business was selected, with help from the East Midlands New Technology Initiative (NTI). The chosen building had two main energy consuming machines; a flow soldering machine and an air compressor. Heat probes were placed on the exhausts of each of the machines, and the building was monitored for two weeks, with a resolution of five minutes. The electricity consumption of the building was also monitored using an optical meter reader. The data provided by the OMR would be used as a comparison against the temperature data.

The main outcome of the experiment was the shape of the temperature graph approximately matched the shape of the electrical demand graph. Brown *et al.*, (2008) mentioned that from this simple experiment, it was found that the energy used by the soldering machine dictated the shape of the electrical demand. Another unexpected outcome was that the compressor ran throughout the weekend, when the building was closed. Brown *et al.*, (2008) explained that this could be due to a leaking air system. The company changed the compressors management system to ensure it would not turn

on during the weekends, and also repaired the air systems. Brown *et al.*, (2008) re-stipulates that even this simple casing temperature test can identify energy usage and hence identify potential energy savings.

The next stage of experimentation was using the casing temperature technique on an appliance. As discussed previously, there are several systems that can monitor total energy consumption, but only a few can monitor individual appliance consumption. The experiment involved analysing a 500W electric heater and measuring the temperature and electrical profiles. A power analyser was used to record the power consumption of the heater, a temperature sensor (Thermochron IButton) was mounted to the heater casing, a secondary temperature sensor was used to monitor the ambient temperature and lastly a timer plug was used to turn the heater on at different time intervals. All the data was fed into a laptop where it was recorded.

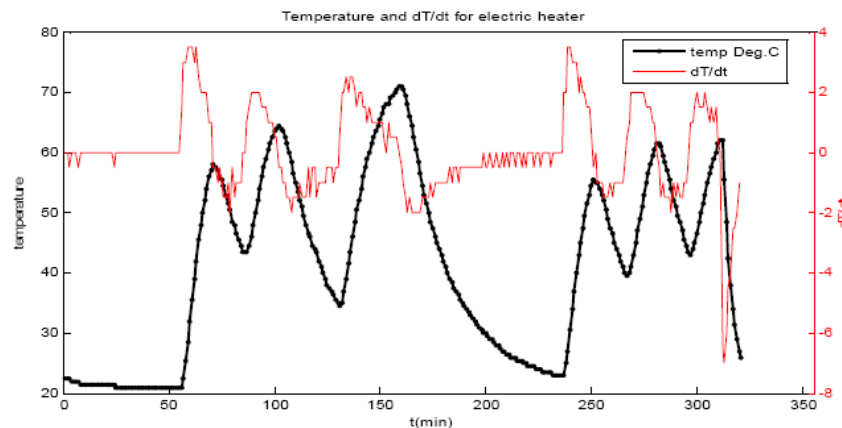


Figure 25 - Heater Experiment results Brown *et al.*, (2008)

The pre-processed temperature results are shown in Figure 25. The figure shows the heater casing temperature varying with time, as well as the dT/dt varying with time. Without processing, it is quite difficult to understand the heaters demand pattern from Figure 25. A slightly clearer on/off graph can be achieved by removing the ambient temperature, but this would still not be very useful. The main problem of using temperature is that it is not a simple on/off variable. When power is applied to the heater, the heater does not reach the desired temperature instantly. It takes a certain amount of time to reach the operating temperature, resulting in a positive slope. The same is true of when the heater is turned off, the appliance slowly returns to the ambient temperature, producing a negative slope. The gradient of these slopes depend on several factors, such as the ambient temperature and the heater material thermal properties. The last issue to consider is whether the heater has a form of standby.

Brown *et al.*, (2008) assumed that if the heater was on standby, the small power drain may cause a slight rise in temperature. This in turn results in the heater never returning to the original ambient temperature. Instead, Brown *et al.*, (2008) created a filter that detects any positive change in slope represents ‘on’ and any negative represents ‘off’. The length of the slopes also represent the on and off times, creating a duty cycle diagram.

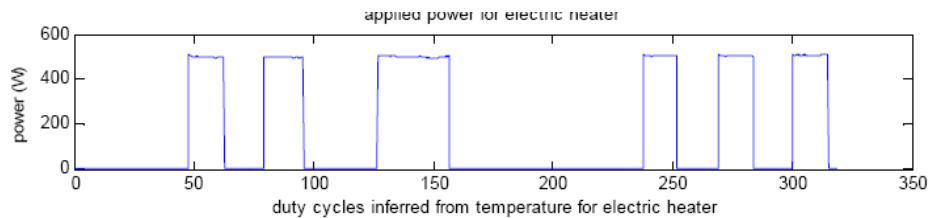


Figure 26 - Duty Cycle of electric heater Brown *et al.*, (2008)

Figure 26 shows the electric duty cycle of the electric heater. After the first stage of processing, it was found that the temperature duty cycle pattern was similar to the electric pattern, but was slightly out of phase. To correct this, Brown *et al.*, (2008) added a secondary filter (low pass filter) to clean up the original signal (see Figure 27).

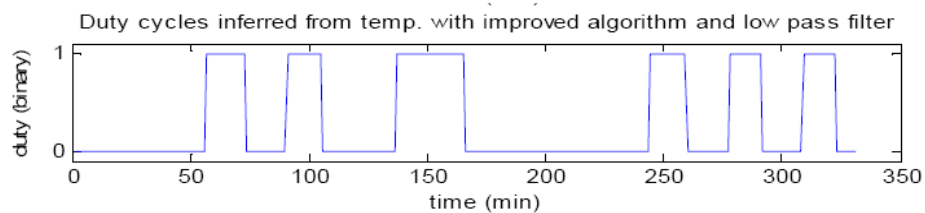


Figure 27 - Filtered Heater duty cycle Brown *et al.*, (2008)

Brown *et al.*, (2008) concluded by stating that with the secondary filter, the temperature monitoring technique proved to be 97% accurate in mapping the duty cycle of an appliance.

The methodology discussed by Brown *et al.*, (2008) achieved several of the criteria stated at the beginning of the article. The case temperature sensors do not interfere with the electronics or power grid, hence are non-interfering, and the sensors are relatively cheap. The main problem with this methodology is that it does not provide a energy consumption graph, unless you treat the on state (‘1’) as the maximum rating of the appliance being measured. In the case of the heater, the on state equals 500W. Another issue is that the data requires post recording processing.

This post recording processing, would require either setting up a generic filter or a unique filter to analyse the data. The last issue with case temperature sensing is that to monitor a buildings energy use, every appliance would need to have a case sensor

attached. This would be uneconomical, even at the low sensor purchase cost. However, it could be argued that to monitor every appliance, to gain a summation of energy use, would require sensors being placed on every appliance. As discussed previously, this could prove expensive. The ideal use of this technology is in conjunction with a total load energy monitor (logger or meter reader). The temperature data, once processed, could allow easier disaggregation of the total demand profile.

2.7.5 STEM TEST

Work by Bryant *et al.*, (2002) investigated an interesting method for electric load identification, known as STEM. STEM, or Short Term Energy Monitoring, is a technique whereby electric load demand is calculated by taking the difference between on and off loads. This means taking the total load of a building, then switching off the interested load, to determine the difference. This difference, according to Bryant *et al.*, (2002), should be the electrical consumption of the interested load. Bryant *et al.*, (2002) stated that the STEM test emerged from the need for building operators to understand where and how energy was being used in their buildings. It was also created to help identify benefits of potential building retrofits.

The key to the STEM test is monitoring total electrical demand. As discussed previously, this can be achieved by using several types of technology. Bryant *et al.*, (2002) discussed using either a meter reading device, such as a pulse optic reader, or using a CT based system. Either technology has to connect to the primary power input or main feed meter. The pre-test stage involves recording basic building data. Bryant *et al.*, (2002) believed that “*the more that is known about the building, the better*”. Bryant *et al.*, (2002) even suggested that talking to maintenance personnel or facility engineers would be extremely beneficial to understanding how the selected building works and the specifications of services (eg HVAC).

The key data to record is equipment lists, lighting fittings and HVAC systems. Also locations of stairwells, light switches, lifts and distribution boards or switchgear are also beneficial. The next pre-test stage is to install the monitoring equipment and a timetable of ‘operations’ constructed. Bryant *et al.*, (2002) stated that the after working hours of the building, usually at night, was the best time to perform the test. This is to minimise disturbance on the buildings operations. There were several steps involved in the STEM test. These are as follows; a) the energy monitoring device is set up, usually with a fine resolution, b) at least two people are required, one to switch off loads, and the other to monitor the recording devices, c) every load is turned on in the building (IT,

lights, fans), d) one load, say lighting, is turned off, e) the electrical monitor is given time to settle and record the new total load value, f) the next load is turned off, and new total electrical demand is recorded. The turning off of the loads continues until all loads are off. Bryant *et al.*, (2002) suggested that a settling time of ten minutes proved adequate in producing a stable data logger value.

As with Brown *et al.*, (2008) a practical experiment was required to determine whether the STEM test could be applied successfully. The Energy Systems Laboratory (ESL), as part of Texas A&M University, was the first building to be selected. The building was comprised of two buildings, a north tower and a south tower. Both towers had to be monitored because they shared a common power source. With the help of volunteer staff, both towers were searched to ensure all loads were switched on. The STEM test for this application was adapted to look at both mechanical and lighting loads. The first three steps of the STEM test were undertaken as discussed in the previous section. The lighting load was then switched off floor by floor, with a time interval between each floor. The next step was to then switch off all mechanical loads in the building. Bryant *et al.*, (2002) commented that it took from 9pm to 5:15am to complete the test. An example of the results produced from the test is shown in Figure 28.

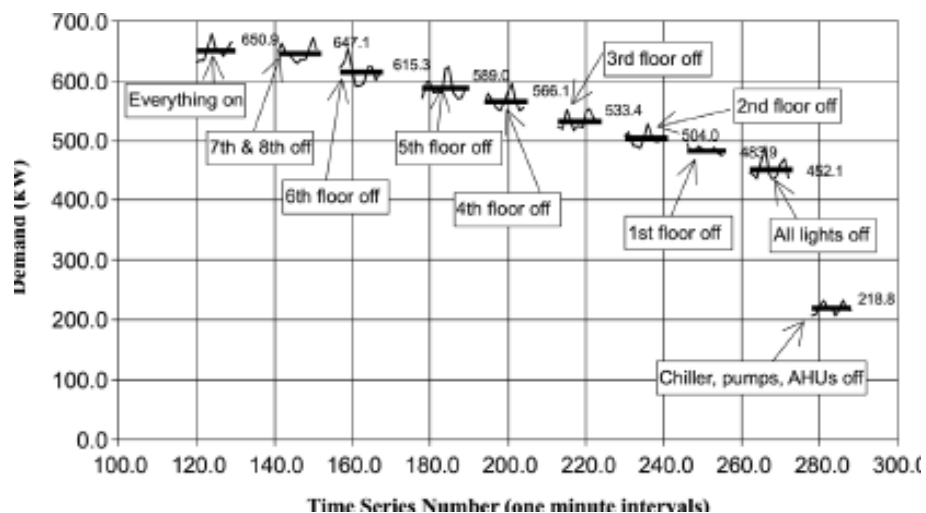


Figure 28 - STEM test results Bryant *et al.*, (2002)

Figure 28 demonstrates the power levels, highlighting full power demand and step reductions in power demand. The change in total demand by switching off different loads is apparent in Figure 28. Bryant *et al.*, (2002) pointed out that it was extremely difficult using the previous energy audit to check the STEM test results. The main reason for the difficulty was due to the differences in how the energy audit and STEM test measure the energy of each load. The energy audit will generally use

maximum or usual loading for each energy user (lights, fans, HVAC). The STEM records the energy use, hence loading, of the energy user at that determined time. An example of the discrepancy between the audit and STEM was given by Bryant *et al.*, (2002). Two 150hp motors in the building were rated at consuming 224kW in the energy audit, whereas the STEM calculated the motors consumed 67kW.

Bryant *et al.*, (2002) believed that during the test, one motor could have been partly loaded, and the other motor was ‘freewheeling’. Freewheeling is where the motor is spinning, but it is under no load (similar to a car engine idling). The 224kW from the audit may have assumed that both motors were under full load. The lighting component of energy use in the north tower was calculated at 410kW and the audit calculated lighting consumption to be 731.5kW. Bryant *et al.*, (2002) believed that the difference was due to emergency lighting and outdoor lighting not being turned off during the STEM test.

An unexpected outcome of the STEM test carried out at the Energy Systems Laboratory was energy saving recommendations being made to the owners of the ESL building. The STEM test determined that the baseload or standby power of the building was 332kW. Bryant *et al.*, (2002) speculated that this could be due to emergency lighting, miscellaneous fans/pumps, vending machines and IT equipment. Bryant *et al.*, (2002) also mentioned that during the test, it was noticed that a high percentage of IT equipment was left on during the night. The recommendations involved taking a survey of the lighting and IT usage at night and determining the percentage of each system. Following the survey, energy reduction programs would be initiated, involving encouraging workers and cleaning staff to switch off lights and IT equipment after use.

A secondary test was carried out by Bryant *et al.*, (2002) in the Engineering Physics Building (EPB) and focused primarily on lighting. The EPB is divided into two parts; a teaching side (lecture halls, laboratories), and an office side (conference rooms, offices). The test determined that the total lighting demand was 277kW. This equated to 6700kWh in the teaching section and accounted for 57% of total electrical consumption. The office side consumed 12365kWh and accounted for 40% of total office electricity consumption. After determining the energy consumption, power associated with lighting and operational hours, Bryant *et al.*, (2002), investigated possible energy saving measures. The main ESMs involved modifying or replacing the current lighting system. Bryant *et al.*, (2002) discussed that there were two possible scenarios for replacing the current lights. The first scenario was to replace the same number of lights and ballast with energy efficient T-8 fluorescent bulbs. With the

replacements, the new lighting load was 61.7kW, compared with the previous 71.9kW. This scenario had the potential of saving 48,528kWh over one year. The second scenario was to replace the existing lights with one T-8 fixture and ballast. This would result in a lighting load of 66.6kW, and had the potential of saving 25,200kWh over one year.

The work carried out by Bryant *et al.*, (2002) achieved two important aims. The first was to demonstrate a methodology that can disaggregate full loads from a total load. Bryant *et al.*, (2002) highlighted that the loads can be broken down into groups, and that the base load can then be determined. Bryant *et al.*, (2002) also pointed out that there can be problems in the calculations if all the loads are not switched off (such as the emergency lights or vending machine during Bryant's tests). The second aim achieved was using the calculated loads, and applying an energy saving measure. Bryant *et al.*, (2002) successfully demonstrated how applying energy efficient light bulbs can save large amounts of energy.

There are several problems with the STEM test. The first problem is that the method only applies to full loads, hence will provide inaccurate results for energy users that are under part loading. Bryant *et al.*, (2002) stated this when discussing the differences between the motor results gained by the STEM test and the results gained from an energy audit. Another problem would be ensuring that every load is turned on and successfully turned off at each stage. For accurate results, every load has to be turned on, and then every load, excluding essential loads (security, emergency lighting), have to be turned off. The last problem is implementing the STEM test. The test has to be carried out as quickly as possible to minimise disruption. Bryant *et al.*, (2002) stipulated that at least two people are needed; one to monitor the equipment, and the other to turn the loads off. Ideally, a large team of people would be needed for large buildings to minimise test time.

2.8 Data Analysis

The previous sections have discussed what load profiles are, the benefits of load profiling and lastly, how to monitor/acquire the energy data. The collected information/data can be used to create a database that in turn can be then analysed to provide information on how energy is being used in the studied building or buildings. Before analysing the data, it is important to ensure that the collected data is accurate, and is a true representation of the building.

When recording any form of data, there is the chance that errors can occur within the dataset. These can be associated with errors within the monitoring equipment, errors within the sensors (or at least an issue with what the sensor is attached to) and how the data is recorded. These different potential issues could result in either no readings or abnormal readings (such as ‘spikes’ or lower than expected values). In order to proceed to the analysis stage, these ‘errors’ have to be removed, or ‘cleaned’ from the data.

There are several techniques that can be used to ‘clean’ recorded data. One method was outlined in both Brown *et al.*, (2010) and Wright *et al.*, (2007). Although the methodology used in both investigations was the same (the same data set was used in Brown *et al.*, (2010) and Wright *et al.*, (2007), hence processed the same), the detail of the data ‘cleaning’ was discussed with varying detail.

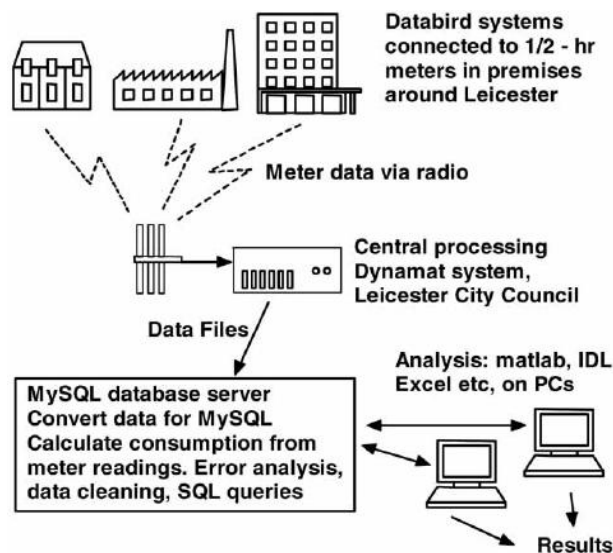


Figure 29 - Diagram of Monitoring Equipment Setup (Wright *et al.*, (2007))

Both investigations used a database, gathered from 300 buildings, based on a half hourly time resolution. Monitoring systems were attached to the building’s electricity meter and the pulses (representing a certain amount of energy consumption) from the meter recorded. These monitors were connected to a centrally located data-logger (or central processing dynamat system), via a radio connection. The number of pulses were counted for each half hour, and hence kWh figures were calculated. The data can then be accessed via a server from ideally from any PC, see Figure 29.

One issue that was found was that the data set suffered from several data quality issues. It was established that there were going to be inevitable data quality issues due to the size of the sampled buildings, and the use of a wireless based system. The main issues that were encountered were periods of zero readings, missing readings, inconsistent values and conversion errors (when the data-logger automatically converts

into kWh, etc). The periods of zero readings was linked to the radio transmission. The large number of sensors required a sending protocol to ensure that the sensors do not send data at the same time. Each sensor has a built in buffer to store the data whilst the sensor is willing to send.

A problem occurs when the radio link between the meter/sensor and central processing dynamat system is lost. This can be called a ‘Dropout’, and can be defined as “when a data unit is logging metering data locally, but is not able to send meter pulses by radio back to the central radio receiver” –Wright *et al.*, (2007)

This results in zero consumption being recorded. When the radio link is re-established, there is a ‘spike’ in energy usage. This spike is due to the saved or buffered meter pulses being summed for one time period. For instance, if between 01:00 and 03:00 there were 100 pulses recorded, and that there was a communication problem in that period. When communication was re-established, the number of pulses for 03:30 could be 100, and the values from 01:00 to 03:00 will be zero. It is very important to remove these ‘spikes’ as if daily profiles are being analysed, then inaccuracies could occur. Figure 30 demonstrates the energy consumption of a building for a year, and highlights several large energy consumption spikes due to this problem.

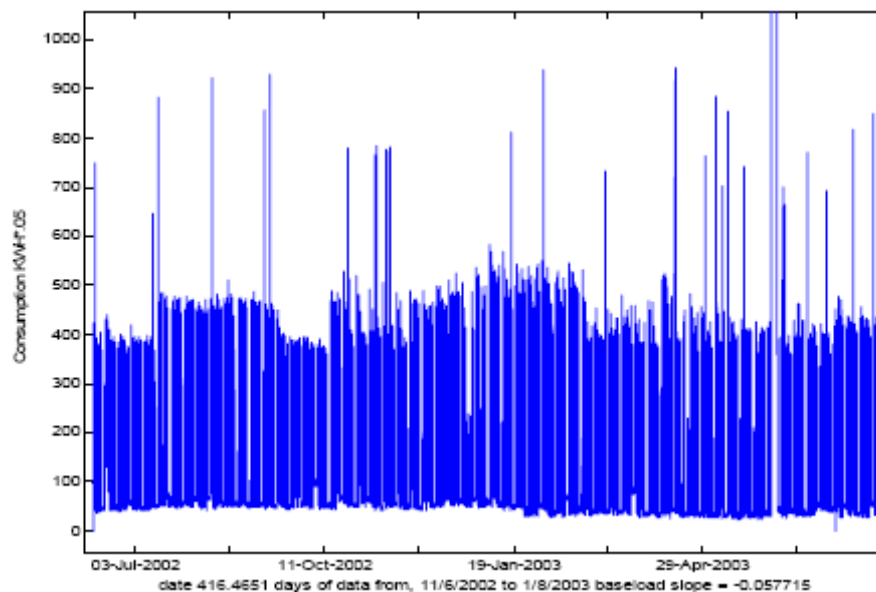


Figure 30 - Example of Large Consumption Spikes - Wright *et al.*, (2007)

There are several stages in ‘cleaning’ and fixing the data. The first was to determine where the data spikes occurred. This involved pairing up the data points in a data sample and calculating the difference between them ($x_i - x_{i-1}$). This difference is then divided by the time period ($t_i - t_{i-1}$), to create an average rate of consumption, f_i , see Equation 2

Equation 2 Data Cleaning Equation, Brown *et al.*, (2010)

$$f_i = (x_i - x_{i-1}) / (t_i - t_{i-1})$$

The standard deviation of the dataset is found, f_t , and as stated by Brown *et al.*, (2010) a multiplier was applied to the standard deviation, to ensure that any legitimate data is not removed. The next stage is to determine the upper and lower limits of f_t , to filter out the spikes. The difference in the consumption f_i , is then compared with the determined upper and lower limits. If f_i either falls between the two limits, or is smaller than the lower limit, then f_i is counted as a valid value. If f_i is larger than the upper limit, then it is discounted. Although this methodology appears to have several steps, if a computer algorithm is designed and applied to the dataset, the ‘cleaning’ stage would not consume too much time.

One issue raised by Brown *et al.*, (2010), is that the previously discussed methodology only indicates where the spikes occur, and removing them is not a simple process. If the values are simply deleted, then there will be large gaps in the data. It could be possible to look at the previous and future values, and then estimate the missing values. As stated by Brown *et al.*, (2010), this was not deemed acceptable as the raw data are recorded as cumulative pulse counts; any missing data will reduce the resolution but not the total consumption.

The indicated ‘out-of-bound’ value is flagged by the cleaning system. The system then takes the calculated energy difference and initially removes the data from the dataset. The data set is then converted back into the meter readings by using a interpolation technique. Figure 31 highlights how effective this cleaning process was, by demonstrating the original data shown by the dotted line, and the ‘cleaned’ data shown by the solid line.

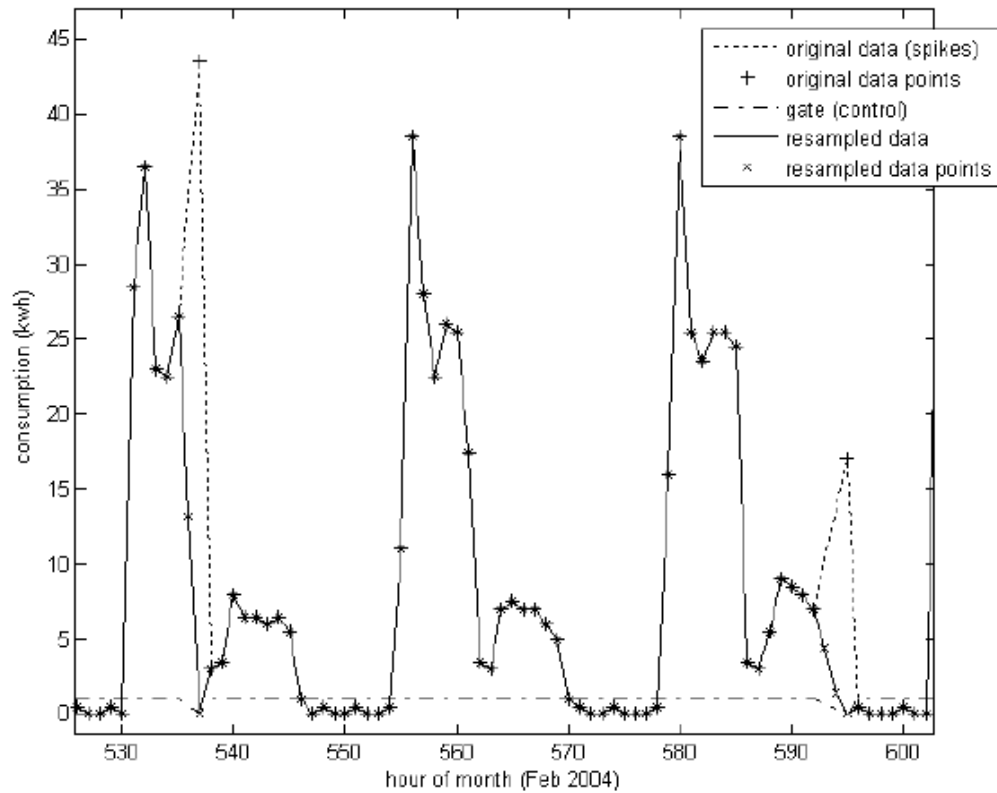


Figure 31 - Example of Original and 'Cleaned' Data, Wright *et al.*, (2007)

One issue with this process highlighted by Wright *et al.*, (2007), is that when several spikes have been removed, then the calculated standard deviation will also change. This resulted in the defined consumption range limits becoming no longer applicable; hence key spikes may not be flagged. To overcome this, the cleaning process was repeated several times, to ensure any unwanted spikes were removed. Brown *et al.*, (2010) stated that if the cleaning process is applied too many times, then the data may become distorted. Simply visually inspecting the calculated profiles is enough to ensure the cleaning process has been successful.

The 'cleaning' methodology outlined in both Wright *et al.*, (2007) and Brown *et al.*, (2010) successfully demonstrated how recorded data can be processed to remove any unwanted data quality issues. These issues included large consumption spikes and missing data. Using an array of statistical techniques, the missing data, and associated large consumption spikes, were removed and the data set adjusted. The end result was a dataset, and profiles, that were predominantly free from errors, and gave a true representation of the building's energy demand.

Work carried out by Stuart *et al.*, (2007) used a database of secondary school energy consumption to determine any changes within the electricity demand. The method is aimed at rapidly detecting any event in a building that alters its energy consumption, and hence determine what caused the identified event. The investigation

was to rapidly analyse data from thirty-nine schools in England, and determine any trends in energy usage, and in turn any occasions where the energy consumption changed. The chosen method was to apply the CUSUM (or Cumulative Summation) technique to the data.

The CUSUM technique is a statistical approach and is defined in Castagliola *et al.*, (2011), as; “*The cumulative sum (CUSUM) control chart has been widely used to monitor the variability of processes. It was introduced by Page (1954), in the case of the mean, and it is used to detect persistent shifts in a process*” (Castagliola *et al.*, (2011))

This technique determines the difference between predicted values versus actual values. Equation 3 demonstrates that the CUSUM statistic S_r is equal to the summation of the difference between a known variable X_i and a constant predicted value μ . As stated by Stuart *et al.*, (2007) “*Plotting the CUSUM of the differences between the variable and the constant can detect small shifts in the process mean*”. This ability to detect and highlight any small changes in a process is very beneficial when investigating trends in energy usage.

Equation 3 CUSUM Definition Stuart *et al.*, (2007)

$$S_r = \sum_{i=1}^r (X_i - \mu)$$

The CUSUM technique was applied to the electrical database consisting of the thirty-eight secondary schools. Before this was carried out, both X_i and μ had to be defined. For one year of school data, there are 17,520 points at a half hourly time resolution. For a database consisting of 39 schools, this amounts to 683,280 points. Processing this amount of data would be time consuming. It was established that key events would last for a minimum of a week, hence analysing at a half hourly resolution would provided little additional information. For that reason Stuart *et al.*, (2007) argued that the dataset can be reduced by adjusting the time resolution. It was decided to sum the half hourly values to produce daily consumptions. The daily consumptions were then converted into weekly consumption, then to four weekly consumptions. It should be noted that the four weekly consumptions do not necessarily represent monthly consumption, due to the varying number of days in a month. Instead blocks of 28 days are summed, producing thirteen data plots per year, per school. Stuart *et al.*, (2007) stated, that some detail is lost, especially on events that last shorter than a week, but time limitations time and the availability of spread sheet software overcame this issue.

The next variable to determine is μ , the constant predicted value. In this investigation, the constant value represents the predicted typical consumption for the

school. There are several ways of determining this value, as stated by Stuart *et al.*, (2007), and Brown *et al.*, (2010) including linear regression based on degree days and other factors. Instead, a recurrent model is used to predict future energy consumption based on historic consumption. Stuart *et al.*, (2007) stated that the simplest way of achieving this is to average all the consumption data, hence treating it as a constant consumption level. This technique can be used for the four week data and the weekly data, but not the daily consumption. The daily consumption varies throughout the week, with the weekend consuming less energy than during the week days. If the daily averages are being used in the CUSUM methodology, then the days have to be averaged together, so taking all the Fridays for example and finding the average Friday consumption.

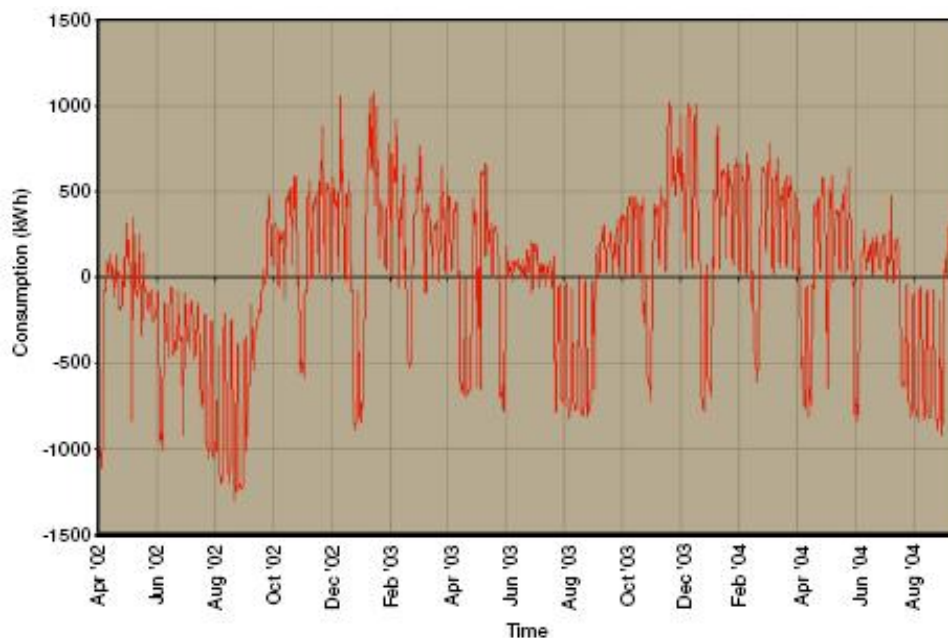


Figure 32 - CUSUM Residual Plot Stuart *et al.*, (2007)

With both X_i and μ being defined, the CUSUM statistic can then be plotted. Figure 32 demonstrates the residual plot, or the difference between the actual and predicted value, for a sample school. The ‘spikey’ nature of the profile demonstrates that there is considerable difference between the actual consumption and the predicted consumption. The negative values are a result of the actual values being smaller than the predicted value. Similarly the positive values are a result of the actual values being larger than the predicted consumption values.

The last stage of the CUSUM technique used in Stuart *et al.*, (2007) was to accumulate the residuals, taking both daily, weekly, monthly and four weekly values and plotting them against time. The consumption was also converted into financial cost,

using £0.05 per kWh. The resulting output is shown in Figure 33, and plots the consumption over a 29 month period.

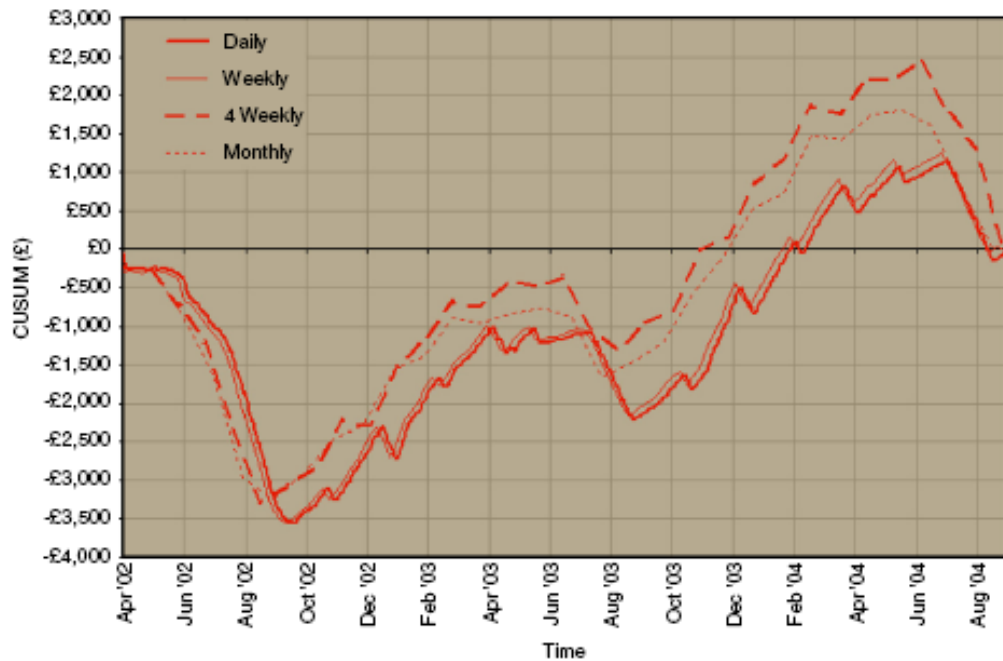


Figure 33 - CUSUM Outcome Stuart *et al.*, (2007)

The CUSUM chart provides quick information about the trends in energy consumption within the school(s). To interpret the chart, the user inspects each of the lines and determines their properties. *“Straight lines represent periods where the consumption pattern is consistent over time relative to the prediction. Positive gradients imply consumption greater than predicted, negative gradients imply lower consumption”* Stuart *et al.*, (2007)

The initial results highlighted in Figure 33, show that there is a viable trend in annual energy consumption. There is less energy consumption than predicted in summer, and more energy consumption in winter, indicated by the positive and negative CUSUM gradients (respectively). The seasonal differences in consumption, as stated by Stuart *et al.*, (2007) are driven by influencing factors on the electric consumption, such as the increased lighting demand in winter. A further observation is the small rise and falls in the gradient (or the small kinks), associated with the school holidays, when energy consumption in the school would drop.

From this initial test of the CUSUM technique, the entire database was analysed. One key observation was that the schools followed a similar pattern, with the profiles showing the same seasonal differences. It was decided to divide the school year into three separate terms that was applicable to all the schools. The three terms, summer, autumn and winter, were treated as separate datasets, as were the holidays that fell in between the terms. The term sections were sub-divided into two, resulting in a total of

twelve average consumption values. This allowed the average consumption for each term and holiday, producing a more accurate result chart.

The new average consumption values were introduced into the predictive, or recurrent, model. The new predicted dataset was compared with the actual consumption data set, and proved to be a very close match (closer than the previous predicted consumption dataset). The new predicted dataset was introduced into the CUSUM technique, with a sample output chart shown in Figure 34.

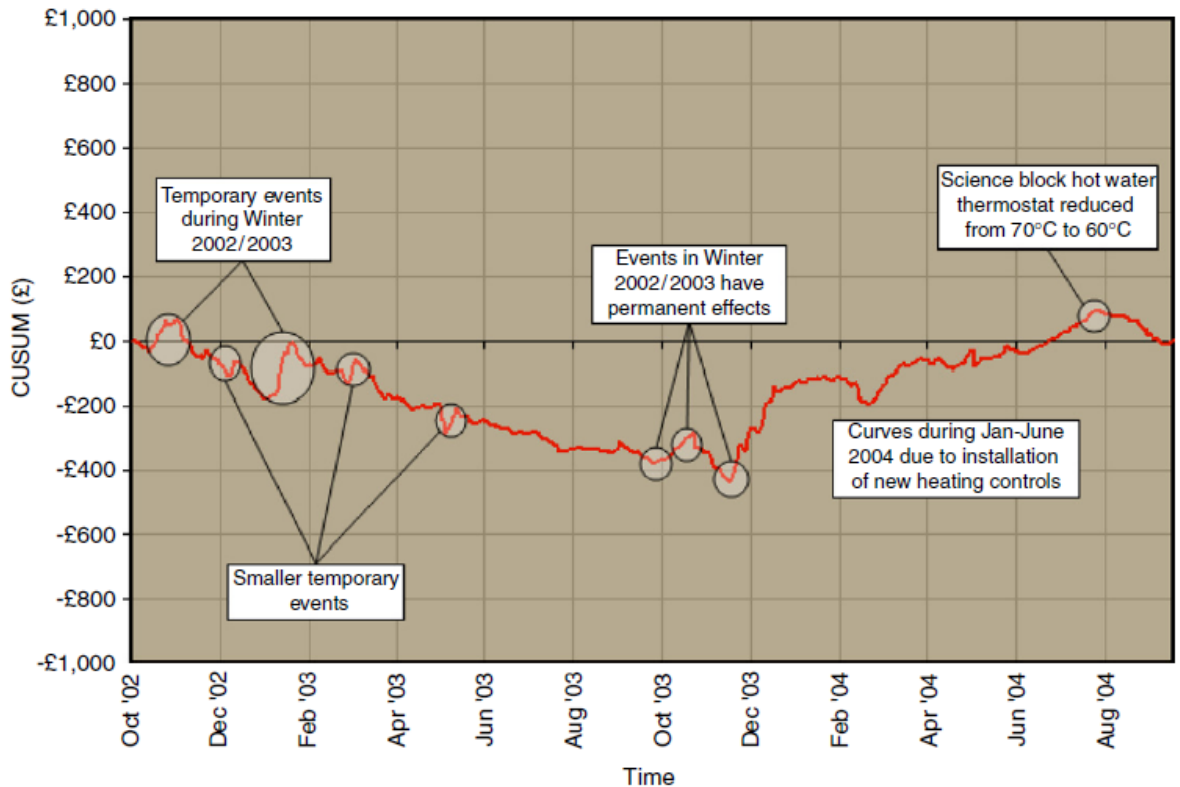


Figure 34 - Improved CUSUM Output, Stuart *et al.*, (2007)

Figure 34 demonstrates a more accurate view of energy consumption events that occurred during the studied time period. This chart can be used as a quick reference to determine if there have been any changes in energy usage throughout the year.

The CUSUM methodology discussed in Stuart *et al.*, (2007) detailed a statistical approach of quickly analysing electricity data. The CUSUM technique can be introduced into spread sheet software, and CUSUM output charts can be produced rapidly. The main benefit to using this technique is that “*clearly identifies an event that would be otherwise missed in a simple visual inspection of the data*”. A major benefit is that the CUSUM methodology can be applied to a large dataset, and ideally any type of building.

2.9 Power Saving and Energy Management

Power management and potential energy savings are an extremely important step in reducing the total energy consumption of a building. The main advantages of investigating power savings are potential financial savings, carbon emission reduction and investment deferral. This section discusses energy savings in both office and school equipment, and the impact of energy saving measures.

2.9.1 Power Management/Saving in Offices

According to Figure 35 (a), equipment can account for around 15% of an office's total energy consumption. If this proportion is analysed further, as shown in Figure 35, it can be seen that PCs and monitors are the most energy consuming devices. As discussed in Junnila, (2007) and Chen *et al.*, (2006), a possible solution would be to replace these systems with low power systems. The PCs could be replaced with EnergyStar rated machines, as discussed in Koomey *et al.*, (1995) or energy efficient laptops, and older Cathode Ray Tube monitors with newer LCD monitors. Each of the replacements offer increased energy efficiency hence decreased energy consumption. Replacing a CRT monitor with an LCD monitor can reduce the energy consumption by two thirds (Carbontrust, (2006c)). However, replacing all office equipment can be extremely costly and not entirely beneficial for a company. A point made by Carbontrust, (2006c), is that although newer PCs may be more efficient than their predecessors. Due to increased performance, newer PCs can actually consume more power. The alternative to replacing current equipment is implementing equipment power management (PM), as discussed in this section.

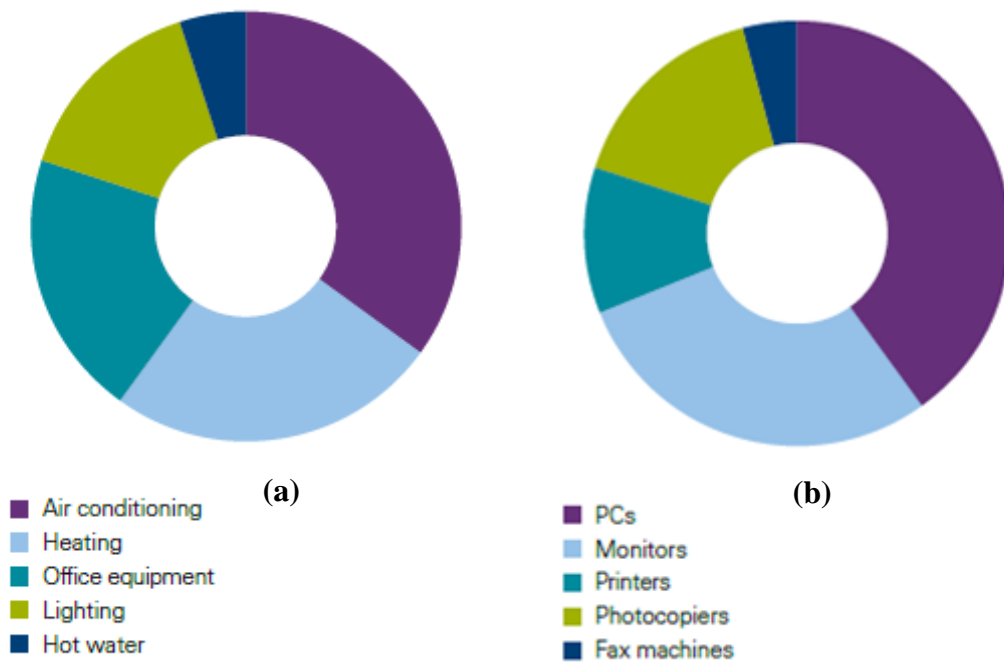


Figure 35 - Total Office Energy Breakdown and Equipment Breakdown use of Energy in an Office, Carbontrust, (2006b)

Figure 35 (b) additionally highlights the breakdown of the 15% of energy associated with equipment use, by different equipment type. From the Figure, both PCs and associated monitors consume around two thirds of total equipment energy consumption.

The majority of office equipment has some form of energy/power management. Power management can range from equipment being turned off when not in use, or being put into a low energy standby mode. The ideal result of implementing power management in office equipment is that energy savings can be found without the need or expense of replacing equipment. The application of power management can be broken down into three different equipment types; PCs and monitors, copiers/printers and fax machines. These categories of equipment although discussed in the office environment, can be applied to any other buildings.

2.9.2 Office Equipment Power Demand

Kawamoto *et al.*, (2001), Kawamoto *et al.*, (2004) and Mungwititkul *et al.*, (1997) provided examples of power use, for standby, active and off, and for either power management enabled equipment or non-power management enabled equipment. Mungwititkul *et al.*, (1997) stated that the active PC with Power Management (PM) power consumption is 48W for Non-Power Management (NPM) and 36W with PM, equating to a 25% saving. The standby power consumption for a NPM PC is 27W. There is NPM enabled PC standby value, because it is assumed that the standby power

demand is as low as it can be. The attached monitors provide little saving when switched to a power management mode, going from 67W with NPM and 66W with PM, equating to a 1.5% power saving. Although this saving appears small, then multiplied by a large number of computers, it becomes more significant. Alternatively, the standby value for the monitor is only 15W, a saving of 77% compared with the active values. There is no mention of what type of monitors were being studied; however the research was carried out in 1996 in which most likely CRT monitors were being used.

		On (W)	Low-power (W)	Off (W)
PC	Desktop	55	25	1.5
	Portable	15	3	2
Display	CRT	85	5	0.5
	LCD	15	1.5	0.5
Copier (monochrome)		185	76	8.7
Laser printer		77	25	1

Figure 36 - Power Demand of Office Equipment, Kawamoto *et al.*, (2004)

The values provided by Kawamoto *et al.*, (2004) also provided an insight into the power consumption of various office equipment. Figure 36 highlights the different on (active), low power (assumed to be standby) and off values for a PC, both desktop and laptops, and for monitors (displays), both LCD and CRT. The relative consumptions for the PCs and monitors vary between Kawamoto *et al.*, (2004) and Mungwitikul *et al.*, (1997). The monitored PCs in Kawamoto *et al.*, (2004) consumed 55W in active, 25W in low power and 1.5W in off mode. As discussed previously, Mungwitikul *et al.*, (1997) measured a PC's power demand at 48W in active and 36W in standby, a difference of 7W and -11W respectively.

A possible reason for the discrepancy could be when each of the research projects were carried out. The research discussed in Mungwitikul *et al.*, (1997) was carried out in 1997 and Kawamoto *et al.*, (2004) in 2003. Computer technology has changed significantly since 1996 (and even from 2003). Larger processors and increasing memory can result in an overall increase in energy use. A more modern PC can use more energy than an older one, when processing the same instructions (Carbontrust, (2006c)). There are also slight discrepancies with the monitor power usage. The recorded power in 1996 for a CRT was 66W, and in 2003 it was 85W. This difference could be the result of CRT monitors in the office becoming larger, in terms of screen size.

2.9.2.1 PCs and Monitors

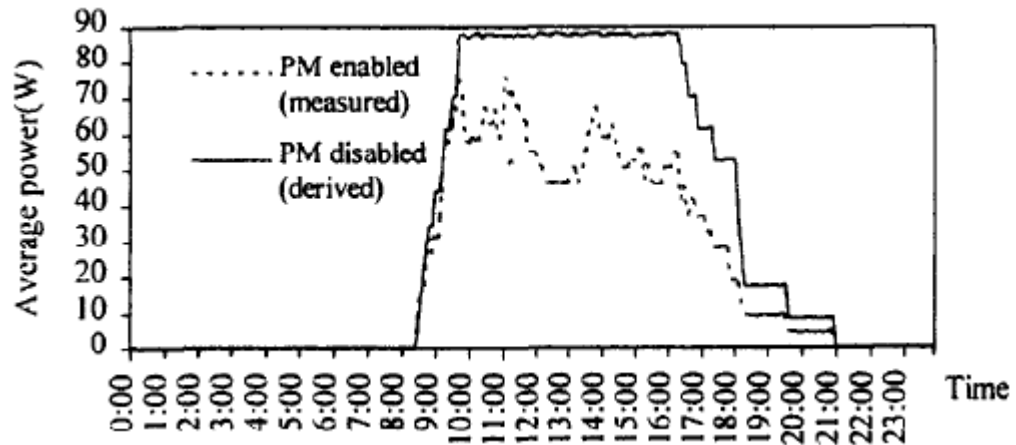


Figure 37 - Example of A power Managed PC, Mungwitkul *et al.*, (1997)

Computers are an important part of a modern office, and it can be assumed that there will be at least one computer per worker (Carbontrust, (2006c)). A single computer left on for 24 hours a day, for a full year, will cost £45 (Carbontrust, (2006c)), although it is unclear what the actual saving in terms of kWhs is. This may seem like a small figure, but if there are one thousand computers left on, this can lead to a substantial waste of money. Simple power management can involve switching off the machines when not in use, such as end of the working day, or if away from the desk for long periods of time. The difficulty with this solution is that it relies on the staff to shut their machines down. Several machines have a built in low power mode, that switches the machine into a hibernation mode. In this mode, the monitor goes into standby, the processor fans shut down and the hard drive shuts down. Only minimal power is consumed to maintain the data kept in the memory. This can be set altering the computers energy management properties. However, access to these computer settings may be restricted in large companies or institutions.

Figure 38 demonstrates the power demand from an average desktop PC. The solid line represents the typical daily use of a PC with no power management. The dotted line represents the same computer, but with power management enabled. There is a significant difference between the two profiles. Both profiles have the same start point, around 0815hrs, and have the same gradient. However the profile with no PM plateaus at 90W from 1000hrs to 1730hrs, whereas the PM profile rises and falls throughout the day. A key event to observe is between 12:00 and 13:00, which represents lunch time. On the non-PM computer, there is no change in energy use during the lunch break, even though it can be assumed that the computer is not being used or that the worker is away from their desk. In comparison, the PM enabled

computer appears to drop down to a set value of around 50W for the lunch break. Figure 38 also demonstrates the benefits of implementing power management on PCs.

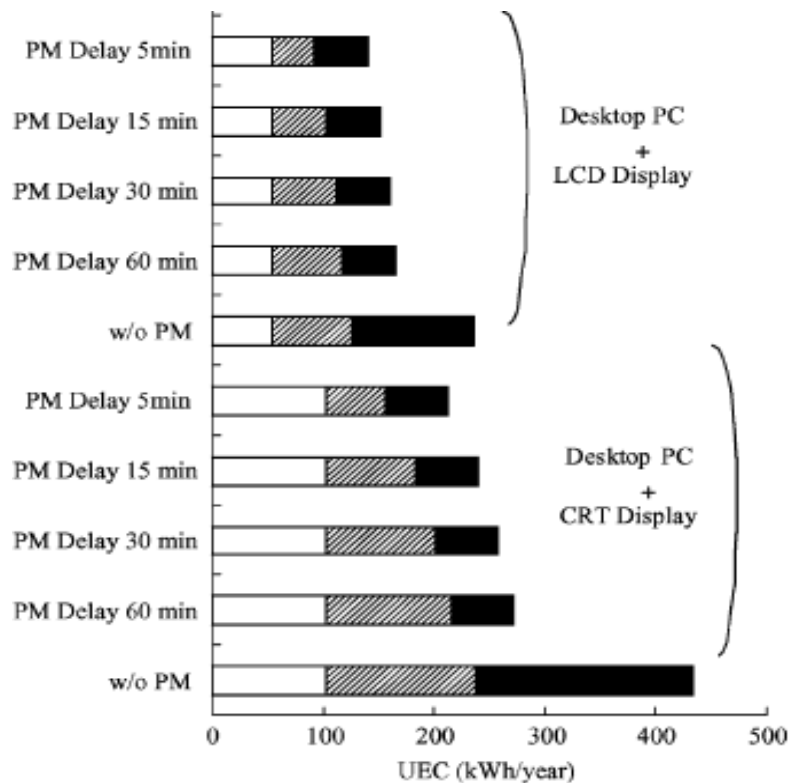


Figure 38 - Energy Consumption of PC's with Varying PM (White=Business Hours, Grey= Idle during business hours, Black= after business hours), Kawamoto *et al.*, (2004)

Figure 38 demonstrates the energy consumption of a PC for different power management scenarios, presented in average annual energy consumption (UEC). The figure can provide three useful insights into power management in offices. The first observation is that there is a clear difference between the PC that uses an LCD monitor and one that uses a CRT monitor. If the non-PM values are investigated, then it can be seen that the CRT machine consumes around 420kWh/yr compared to an LCD machine that consumes 250kWh/yr. This confirms both Chen *et al.*, (2006) and Junnila, (2007), in that energy savings can be found by replacing current equipment to newer energy efficient systems. The second important discovery found in Figure 38 is that slight differences in energy consumption can be found using different PM delay times. The delay time can be defined as the time between the point when the user stops using the machine and the point when the machine switches to a low power or standby mode. There are five delay stages used in Kawamoto *et al.*, (2004) investigation, 5 minute, 15 minute, 30 minute, 60 minute and off. The off, or “without power management”, stage is used to determine a non-power management benchmark. It is with this energy benchmark that the other power management interventions can be compared and their relative impact determined.

The last useful piece of information given by Figure 38 is how the different levels of PM affect the various stages of the day. It can be assumed that the three stages represent the machine working during office hours, the machine in standby mode during office hours and finally the machine idling outside working hours. Figure 38 demonstrates that the different levels of PM appear to only affect idling and out of work hours. When either PC is compared, the non-PM modes consume around 420kWh/yr and 250kWh/yr compared with the first level of PM which consumes 280kWh/yr and 180kWh/yr, for CRT and LCD respectively. By implementing a PM delay of 60 minutes, a 60% or 64% energy saving can be achieved for CRT computer and LCD computers respectively.

A possible explanation for this reduction in energy use could be how the machine is used. If the PC is left on during out of office hours, then it will naturally consume more energy than if it was turned off, or in a low power mode. By simply initiating standby mode on the PC, the energy consumption can drop dramatically. The PC will still consume energy but not as much if it was just left on in normal operation mode. The PM also affects the idling section. It can be assumed that when the PC is not turned off or if not being used, such as during break times, then the computer can be classed as “idling”. For the CRT computer, the difference in energy consumption between a PM delay of 60 minutes and 5 minutes is around 40kWh/yr, whereas the difference for the LCD computer is around 20kWh/yr. The impact of PM on the idling stage is smaller than that of the after hour work, though this is most likely due to the computer idling for less hours compared with being left on after work. It can be seen in Figure 38 that energy consumption for when the computer is left on during working hours remain constant regardless of the different levels of PM. The only way this consumption would change would be if the implemented PM involved changing the operation power demand.

Similar work on power management was carried out by Mungwitikul *et al.*, (1997). The discussed research investigated applying one level of power management to determine the energy savings. The methodology differs from that discussed in Kawamoto *et al.*, (2004) in that the equipment were monitored for a sample day and extrapolated to create annual consumptions. This extrapolation provides annual standby, active, suspend and off percentages for the year. Additionally, by monitoring the individual equipment, the actual standby, active, warm up, and suspend power demands can be determined. With the addition of walk round surveys and occupant

interviews, a further insight into how and when equipment was being used in the office was gained.

The discussed research does not highlight why the PM disabled PC in Figure 38 is derived and actually measured. One reason could be that the power management functions cannot be switched off. Recorded measurements for active, standby and off power use for the PC could be used to create an approximation of how a non-PM enabled PC would behave.

A different approach into energy efficiency in offices was carried out by Koomey *et al.*, (1995) and focused on energy consumption in US offices, with the guide of improving efficiency in office equipment. Detailed equipment usage was determined by using monitored consumption data, equipment density and estimated appliance usage. There are some similarities between the research carried out by Koomey *et al.*, (1995), Mungwitikul *et al.*, (1997) and Kawamoto *et al.*, (2004). The same concept of monitoring the active, standby and off modes is covered by each of the research projects.

Koomey *et al.*, (1995) included another category called ‘suspend’, which could be assumed to be a state between active and standby, and renamed ‘off’ to ‘plug’ mode. A key difference of Koomey *et al.*, (1995) is that it looks at various equipment, in regards to different baselines, opposed to different power management settings. There are four baselines used in Koomey *et al.*, (1995); 1990 stock, 2005 baseline, Energy Star and advanced. The 1990 baseline was based on industry set standards, and the 2005 baseline was determined by extrapolating industry projections on equipment ownership and usage. The EnergyStar baseline was determined using the EnergyStar guidelines, and the advanced baseline represents the optimum or best practice equipment usage.

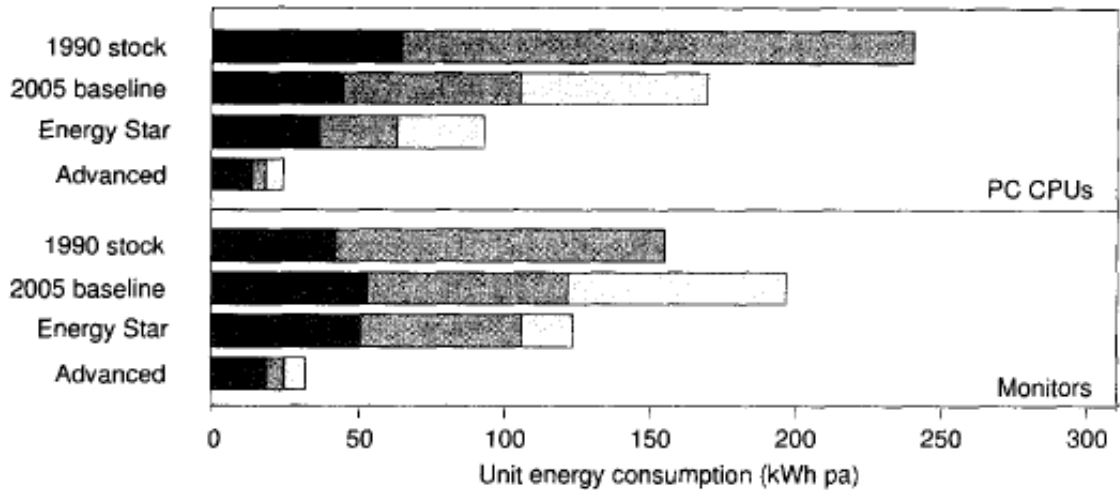


Figure 39 - Comparison Between Different Energy Saving Potentials (White=Business Hours, Grey= Idle during business hours, Black= after business hours), Koomey *et al.*, (1995)

Figure 39 demonstrates the results from the research project. The black area represents the active portion, the grey represents the standby portion and the white represents the suspend portion. The results show the different energy consumptions of both PCs and monitors, for each of the four baselines. The 1990 baseline is used as the pre-intervention benchmark. Without intervention, the PC consumes under 250kWh/yr, consumes 170kWh/yr against the 2005 baseline, under 100kWh/yr with EnergyStar and consumes about 50kWh/yr with advanced setup. In comparison, Mungwititkul *et al.*, (1997) calculated annual PC consumption at 60kWh/yr, which is a 190kWh difference. This large difference could be due to different PC technology or monitoring methods.

Both research projects used extrapolation techniques to create annual consumption data. Different extrapolation techniques could result in different values. The remaining consumption values include the ‘suspend’ mode which appears to replace the standby consumption. Koomey *et al.*, (1995) commented that the difference between the 2005 and 1990 consumption figures is caused by the reduction in processor/microchip power use. Further explanation is needed to define what the difference between standby and suspend modes, in order to understand the energy savings. Figure 39 highlights that the main savings can be found in the standby and suspend modes, a similar conclusion drawn by Kawamoto *et al.*, (2004) and Mungwititkul *et al.*, (1997).

Figure 39 additionally highlights the energy consumption of computer monitors. The Figure shows that the 1990 stock value is 150kWh/yr, the 2005 baseline is 200kWh/yr, the EnergyStar is 120kWh/yr and the advanced is 25kWh/yr. It is interesting to note that the 2005 consumption is 50kWh/yr more than the 1990 stock

value. Koomey *et al.*, (1995) stated that this increase is due to an increased use of full colour monitors, as well as larger monitors. Similarly to PCs, the main savings are in when the computers are in suspend and standby modes.

If the monitor and PC consumption values are combined together, comparisons can be made to Mungwititkul *et al.*, (1997) and Kawamoto *et al.*, (2004). The total PC and monitor total energy usage is 400kWh/yr for 1990 stock, 370kWh/yr for 2005, 200kWh/yr for EnergyStar and 45kWh/ for advanced mode. Kawamoto *et al.*, (2004) calculated a PC with a CRT monitor consumes 420kWh/yr without PM and 220kWh/yr for the same computer with PM enabled (at minimum delay time). The 1990 stock value and the NPM computer value are very similar, with only a 5% difference. The slight variation could be due to difference in technology between the 1990 level and the NPM computer, such as increased processor size and increased memory. The values for the EnergyStar PC and monitor are also very similar to the PM enabled PC, with only a 20kWh/yr difference. It could be assumed that the methodology proposed by Koomey *et al.*, (1995), did not take into account the use of LCD monitors for the 2005 calculations, due to the limited availability of LCD monitors.

It could be assumed that the computer systems (both base units and monitors) discussed in Mungwititkul *et al.*, (1997) and Koomey *et al.*, (1995) are of a similar specification due to the year the research was carried out is the same. The methodology used in Kawamoto *et al.*, (2004) investigated a modern PC (though this is an assumption based on the time of the investigation) and then monitored the energy consumption of the PC with no PM. As discussed previously, although modern PCs are more energy efficient, they can consume more power than earlier computers, such as the ones that could have been used in the other studies. This could account for the differences in energy consumption.

2.9.2.2 Copiers/Printers

The methodology for monitoring the energy consumption associated with photocopier use varied from the previously discussed method. Kawamoto *et al.*, (2004) discovered that unlike a PC, a photocopier/laser printer's energy consumption cannot simply be monitored and hence firm conclusions established. The difficulty in monitoring laser printers, according to Kawamoto *et al.*, (2004), is that laser printers need their rollers/fusers heated up periodically to maintain operating temperature for when the printer is used. This is to ensure that the printer/copier can be used quickly and to reduce the warm up time. Kawamoto *et al.*, (2004) and Mungwititkul *et al.*,

(1997) stated that this difficulty arises when trying to distinguish between the rollers heating up during the maintenance cycle and the rollers heating up for actual printing. The two events have very similar energy use profiles, and if confused, the resulting energy savings from applying power management may be overestimated. This confusion occurs when trying to determine whether the photocopier event is a standby event or a usage event. An example of a demand profile for a laser photocopier is shown in Figure 40.

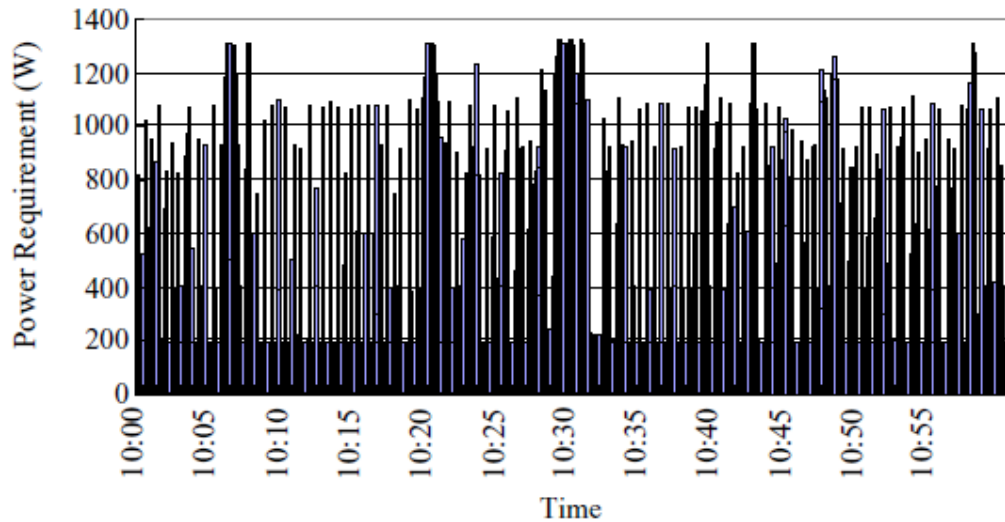


Figure 40 - Power Demand Profile for a Laser Copier, Kawamoto *et al.*, (2004)

The implemented solution involves monitoring the paper use of the copier. It is assumed that if the copier is actually printing, then there will be an energy spike associated with the rollers being heated and paper being used. If the printer is on a maintenance cycle, then it will have the same energy spike for heating up the rollers but there will be no paper use. The solution discussed by Kawamoto *et al.*, (2004) was to use vibration sensors mounted to the side of each copier to monitor when the printer was being used. The number of pages printed, hence amount of energy used, was extrapolated from the recorded data (example of data shown in Figure 41). The number of pages printed was estimated to calculate the number of pages printed per hour and hence total daily printing energy consumption.

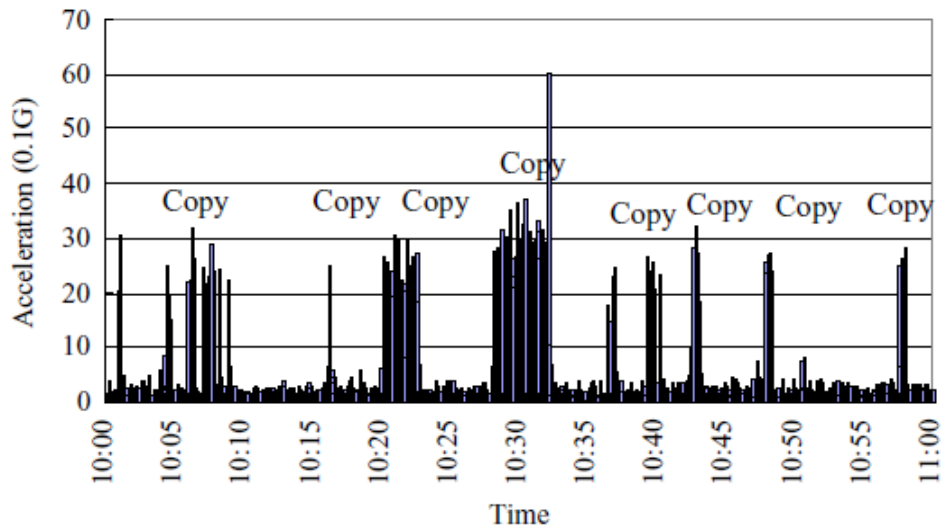


Figure 41 - Vibration Data for a Laser Copier, Kawamoto *et al.*, (2004)

The potential energy savings for photocopiers is shown in Figure 42. Although not stated, it can be assumed that the photocopiers are laser based, and not inkjet/bubble jet based. According to the study, with no intervention, a photocopier's total annual energy use equated to over 1,100kWh. This total is broken down to 47% of energy consumption occurring during out of hours, 48% occurring during business use (though at idle, not at use) and the remainder associated with actual photocopier use. With power management turned on, the out of hours energy use is reduced by 90%. The effect of power management on business idling hours, is minimal for all time delays, bar five minutes, which when implemented saved 35%.

A reason for the small impact on in business idle use was discussed in Kawamoto *et al.*, (2004). Even on the smallest time delay, the power management would only initiate after five minutes. If the copier was used every four minutes, the power management would never activate, resulting in the photocopier not being switched into a low power mode. The consequence of this is that there will be no energy savings during business hours, and the power management in relation to business hour idling, is ineffective.

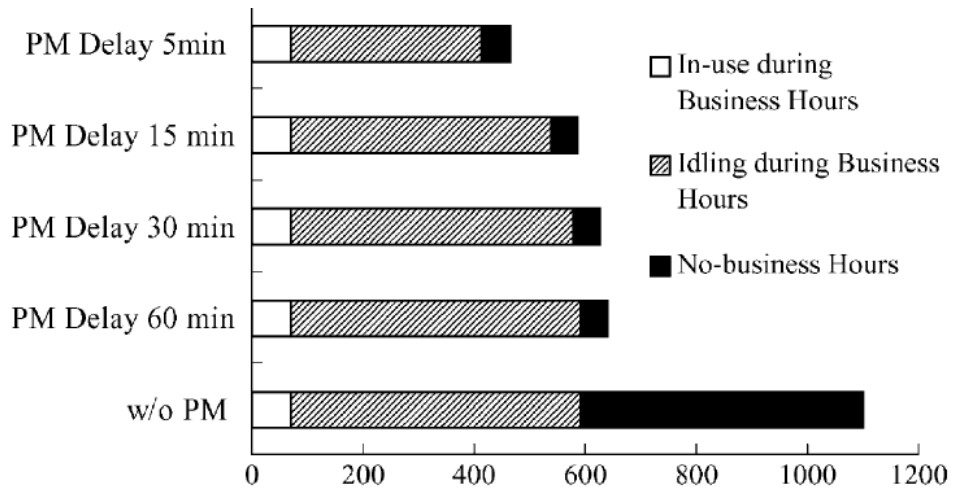


Figure 42 - Potential Energy Savings for Copiers, Kawamoto *et al.*, (2004)

With five minute delay power management engaged, the total energy consumption of the photocopier dropped from over 1,100kWh to 550kWh. The low power mode/standby mode of photocopiers can vary, from 35W to 76W. One solution could be to switch off the photocopier completely hence saving 35-76kWh. However the time for warm up after being turned back on may not be practical for a company as it can take up to five minutes or longer for the copier to warm up.

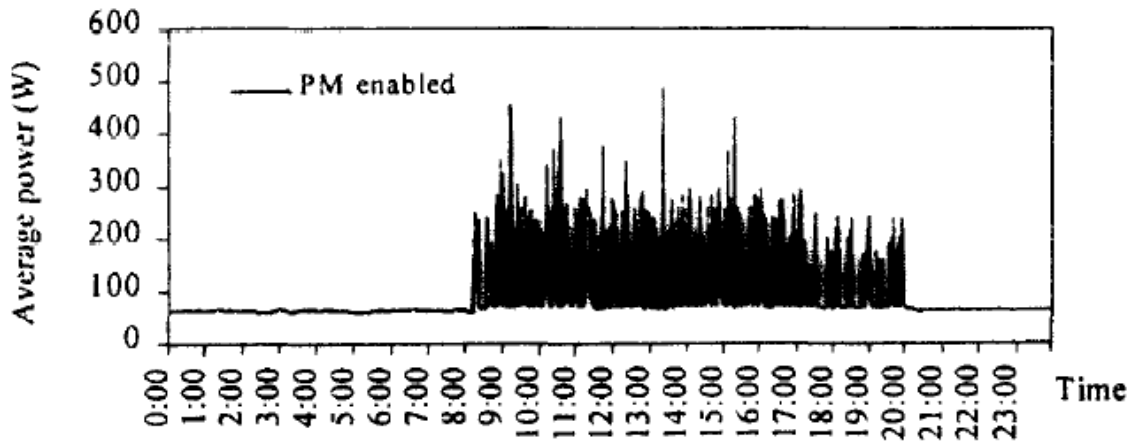


Fig. 4. Typical weekday load pattern of a copier.

Figure 43 - Power Demand Profile for a Copier, Mungwitikul *et al.*, (1997)

A typical daily power demand profile for a copier is shown in Figure 43. From the profile it can be seen that there is a 80W standby, an average active use of around 220W and a peak demand of 500W. The profile also demonstrates that the copier is not switched off during the night, as shown by the continual power demand from 00:00 to 08:00 and 20:00 to 23:59. According to Mungwitikul *et al.*, (1997) a photocopier can have a 94% idle loss (the ratio of on-time minus active time over on-time), and by enabling the power management feature, 20% of the standby energy consumption can be saved. A NPM enabled copier can consume 859kWh/yr versus a PM copier that

consumes 754kWh/yr. These figures can be compared with Kawamoto *et al.*, (2001) (874kWh/yr), Koomey *et al.*, (1995) (880kWh/yr) and Kawamoto *et al.*, (2004) (1100kWh/yr). An interesting point stated by Mungwitikul *et al.*, (1997) is that a PM copier remains in active mode more often because of the longer associated ‘recovery’ time. This ‘recovery’ period is not actually discussed but could be assumed to be the time it takes a copier to go from the standby state to the active state (warming up the rollers).

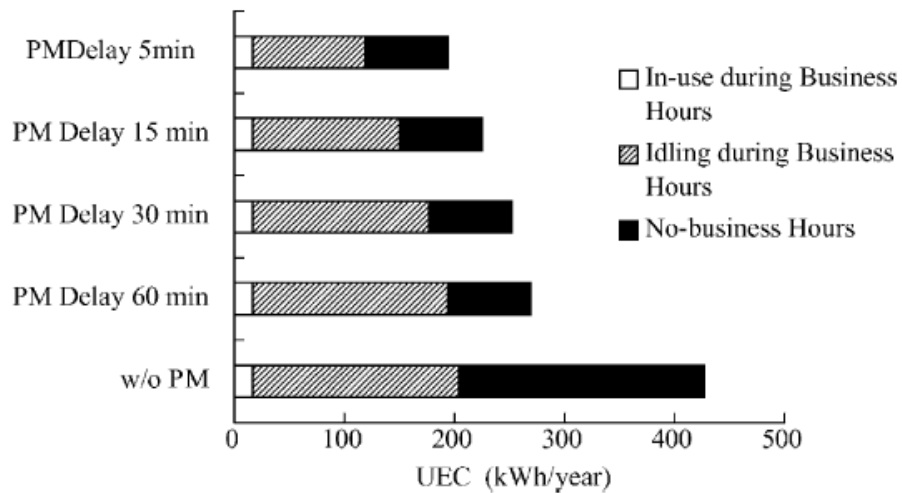


Figure 44 - The potential Energy Savings of a Laser Printer, Kawamoto *et al.*, (2004)

Printers were also investigated in the research carried out by Kawamoto *et al.*, (2004). Similarly to the photocopiers, the discussed printers are laser based opposed to inkjet/bubble jet based. The same methodology was carried out on laser printers as was applied to the laser photocopier, due to both using a heating cycle to maintain a set temperature in the rollers. However, it was found that the vibration sensors did not pick up every printing event, due to the movement not being strong enough. The vibration sensors were replaced with infra-red sensors mounted to the output paper tray. A similar extrapolation technique used on the copier vibration monitoring was applied to the infra-red sensor data. This data was used in conjunction with the energy data to determine the pre-power management benchmark.

Figure 44 shows the results from monitoring one laser printer. The total annual energy consumption is over 400kWh/yr without any power management interventions. This total consists of 50% of energy used out of hours, 45% of energy used during business idling and 5% associated with actual printer usage. Figure 44 demonstrates that the majority of energy savings associated with power management are found in the out of hours usage. By applying a five minute delay in power management the study

found that this resulted in around 65% energy savings in the out of hours usage, and 45% savings during business hours idling energy consumption.

Mungwititkul *et al.*, (1997) discovered that there is a 98% idle loss in a laser printer, and by implementing the PM features, 50% of the standby energy consumption could be saved. This standby saving results in a 55% energy saving on the total annual consumption. The results calculated by Kawamoto *et al.*, (2004), Mungwititkul *et al.*, (1997) determined that a laser printer with no PM, consumes 303kWh/yr and a PM enabled printer consumes 136kWh/yr.

Koomey *et al.*, (1995) also investigated the annual energy consumption of laser printers. The results are shown in Figure 45. The 1990 stock and 2005 baseline consumption is over 250kWh/yr, the EnergyStar consumption is 110kWh/yr and the advanced is 25kWh/yr. The stock energy consumption of 250kWh/yr is considerably lower than that found by Kawamoto *et al.*, (2004) (420kWh/yr) and Mungwititkul *et al.*, (1997) (303kWh/yr) and Kawamoto *et al.*, (2001) (283kWh/yr). There are several possible explanations for the differences between each result. A similar explanation for the laser printer consumption can be found in found in the PC consumption variations. It should be noted that the research by Kawamoto *et al.*, (2001), Kawamoto *et al.*, (2004) and Mungwititkul *et al.*, (1997) were carried out in different years. Equipment technology and usage has changed dramatically, as PCs became more popular and available in offices.

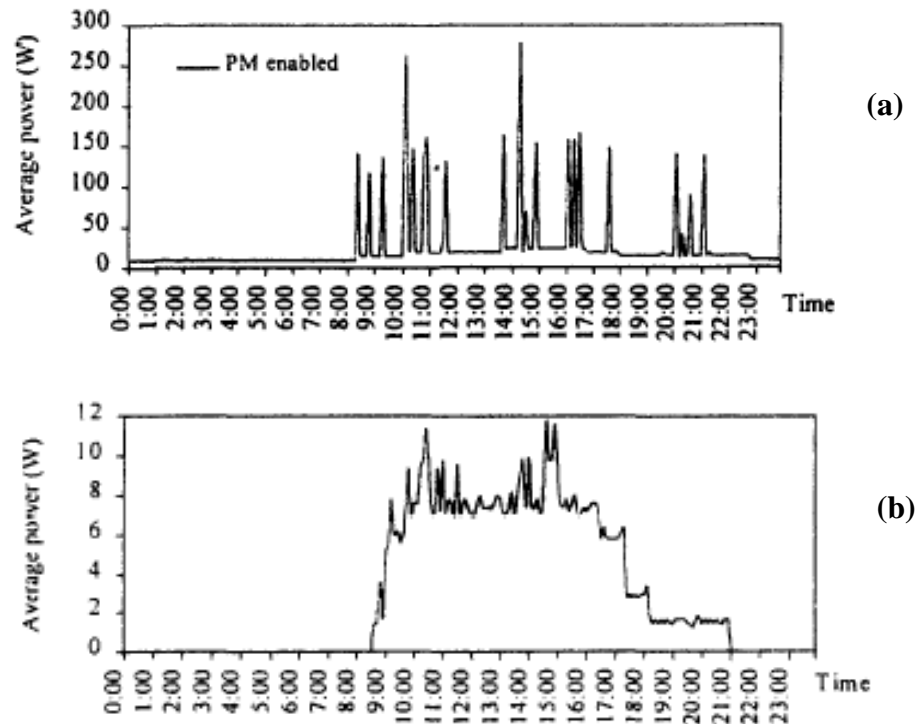


Figure 45 - Power Demand Profiles for a Laser Printer (a) and a Dot Matrix Printer (b), Mungwititkul *et al.*, (1997)

A comparison between laser printers and the inkjet/dot matrix equivalent printer can be found in Figure 45. The top graph (a) shows the average daily power profile for a laser printer and the bottom graph shows the average power profile for a dot matrix printer (b). Figure 45 highlights the peak power demand differences between the two technologies. The laser printer appears to have a peak demand of around 250W, though this figure will be dependent on the number of pages being printed. The dot matrix printer appears to have a peak demand of 12W, a difference of 238W or ~1800% difference. Another key difference between the two profiles is the active time period. The laser printer power profile has a steady standby value and then peaks to several hundred watts for a short duration. Alternatively, the dot matrix's power profile shows either a larger standby value or longer active time.

Kawamoto *et al.*, (2001) also demonstrated the annual energy consumption differences between inkjet and laser printers. The average energy consumption of an inkjet was 74kWh/yr, versus the laser printer (283kWh/yr). By comparing standby, active and off power values for each printer technology a clearer understanding of the associated power use can be gained.

It should be noted that for PCs, photocopiers and printers, there are no energy savings gained in terms of actual equipment usage. Only by implementing other forms

of operational power management could additional savings be gained. Examples of such power management could be draft toner mode and eco printing modes.

2.9.2.3 Fax Machines

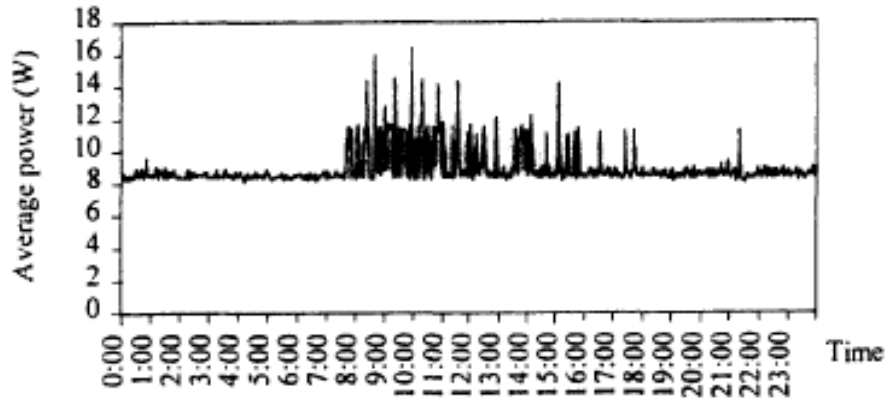


Figure 46 - Power Demand Profile for a Fax Machine, Mungwitkul *et al.*, (1997)

Figure 46 demonstrates an average power demand of a fax machine. The demand profile shows that the machine is left on throughout the day, as shown by the continual standby value of 8W. It can be assumed from the demand profile that the fax machines are thermal based, i.e use thermal sensitive paper, opposed to laser based. The peak demands reach a maximum of around 16W, compared with a laser copier/printer that can reach up to 250W. This can also be confirmed by investigating the average active and standby energy values for each of the two different technologies. A thermal fax machine consumes 124kWh/yr in active mode and 14W in standby, and the laser equivalent consumes 326kWh/yr. Additionally, Kawamoto *et al.*, (2001) calculated the average energy consumption of a fax machine was 119kWh/yr, which when compared with that of Mungwitkul *et al.*, (1997), it could be assumed that it is a thermal based fax machine.

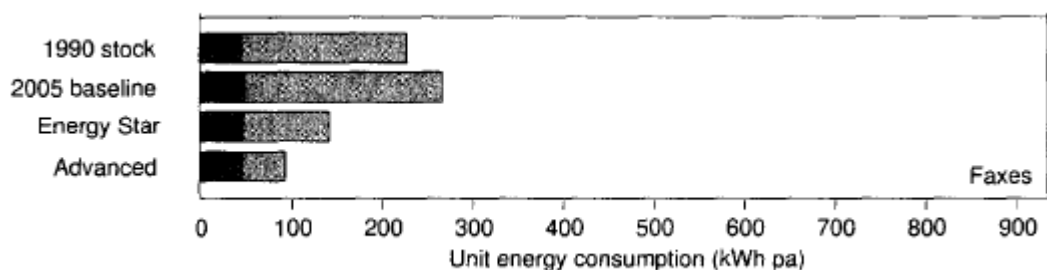


Figure 47 - Potential Savings for a Fax machine, Koomey *et al.*, (1995)

The potential energy savings vary according to the different power management systems applied. Mungwitkul *et al.*, (1997) discovered that an average fax machine can have an idle loss of 98%, due to the fact that the fax machine has to be left on in

order to receive incoming faxes. With the available power management mode activated, the overall energy savings could reach 53%. The research discussed in Mungwitikul *et al.*, (1997), does not describe what power management features were available on the fax machine, and what the power saving features actually changed. Similarly, Koomey *et al.*, (1995) calculated that there was a 50% energy saving between the 1990 stock value and 2005 baseline (with the basis that the 2005 standards incorporate PM), see Figure 47. Similarly to the other research projects, the main energy savings are found in reducing the standby energy consumption.

2.9.2.4 Other Equipment

Mainframe computers, or servers, can store backups of user computers, archived data and online data content, and are generally used throughout the day and year, with little off time. Koomey *et al.*, (1995) researched the annual energy consumption of a mainframe computer, in both terms of 1990 stock value and 2005 baseline. The 1990 stock level for a mainframe was calculated at 140,000kWh/yr, with 90,000kWh/yr associated with active energy use and 50,000kWh/yr associated with standby energy use. The 2005 baseline was calculated at 60,000kWh/yr with 40,000kWh/yr associated with active energy consumption and 20,000kWh with standby. Kawamoto *et al.*, (2001) investigated equipment in US offices and calculated annual mainframe energy consumption in 1999 at 58,400kwhr, which is a close match to the 2005 estimated consumption stated in Koomey *et al.*, (1995). Considerable energy savings could be achieved if the standby energy consumption could be lowered. The difficulty with this is that the mainframe is generally on all the time, and may only enter standby occasionally.

2.9.2.5 User Interaction

There has been several research studies dealing with the potential savings of power management applied to office equipment and other non-domestic buildings. One potential barrier for an office adopting energy saving measures is how the user interacts with the equipment and whether power management can actually be initiated. Mungwitikul *et al.*, (1997) discovered that in the case of PCs, around 90% of the studied machine, no form of power management was turned on. In most cases the BIOS setup screen on the PC, or the monitor properties, were not accessible by the users. Additionally Mungwitikul *et al.*, (1997) and Webber *et al.*, (2006) discussed that several operating systems would not go into standby mode when connected to networks,

which the majority of office PCs are networked. It was also found that in 90% of monitored photocopiers the PM systems were not enabled.

	Manual-off rate in non-business hours (%)
Portable computer	97
Desktop computer	82
Display	60
Copier	55
Laser printer	55

Figure 48 - Percentage of “Manual off rate” for Office Equipment, Kawamoto *et al.*, (2004)

Additionally, some office equipment relies on the users to switch them off, if no form of PW is available, or to further reduce the energy consumption of the equipment (i.e off power consumption). Figure 48 highlights the various amounts of manual turn off rate for different types of office equipment. The manual turn off rate can be defined as the amount (as a percentage of business hours in this case) a piece of equipment is turned off manually. From Figure 48, it can be seen that portable PCs have the highest manual off rate, whereas laser printer/copiers have the lowest rate. This can be explained by examining how each technology is actually used. Generally when users are finished using laptop computers, they close the laptop’s lid, thus turning it off. Printers/copiers are generally used by more than one worker (networked printer), hence users may be more reserved in switching off the printers, in case others may use it.

The comparison between the percentages of manual off rate is made between a typical US office and a typical Japanese office. It can be seen, that the Japanese office has a higher rate of manual turn off than the US office, in each of the different pieces of equipment. The US appears to have half the manual off rate than the Japanese equivalent office. This could be due to more stringent energy measures in the US or the increased use of enabling an automatic turn off function.

2.9.2.6 Overall Affects of Power Management

By implementing or activating different power management systems into the various office equipments, an overall energy saving can be achieved. Mungwitikul *et al.*, (1997) calculated that equipment in an office can account for 2.2-5.6% of the total energy consumed by the office. Additionally, it is noted that by implementing power management in equipment, and increasing worker awareness of energy efficiency, there could be up to a 26% energy saving. Furthermore, this decrease in energy consumption

would not cost the company. Work by Koomey *et al.*, (1995) confirmed that office equipment can account for up to 7% of total energy consumed in an office.

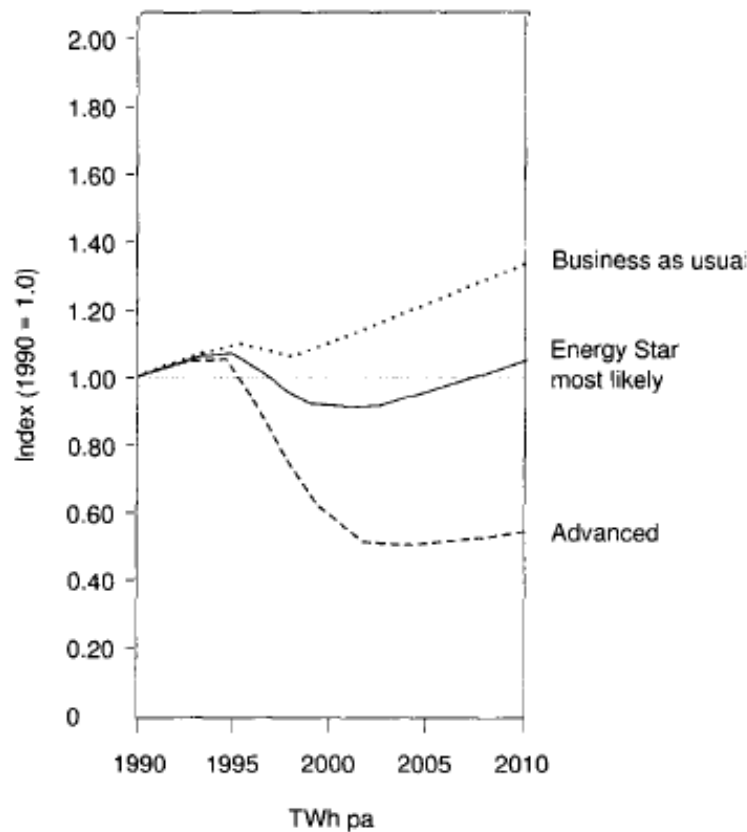


Figure 49 - Trend in Office Equipment Energy Usage, Koomey *et al.*, (1995)

Koomey *et al.*, (1995) also investigated the cumulative effects of different energy saving measures. Figure 49 demonstrates the annual energy consumption of offices from 1990 to 2010, versus the 1990 base value or index. The figure highlights that if nothing is done to improve energy efficiency in an office (i.e. “business as usual”), the overall consumption increases by 40%. If the majority of equipment is EnergyStar rated then the energy consumption by 2010 increases by only 10%. Both the ‘business as usual’ and the EnergyStar profiles appear to drop in 1995 and start to rise by 2000. This dip and rise could be the result of previous equipment being replaced with modern (hence assumed more energy efficient), resulting in a decrease in energy consumption. The rise could be the number of different office equipment being increased. The advanced profile drops down to 0.5 by 2003 and then slowly rises. The drop and rise are most likely the result of the same reasons for the business as usual and EnergyStar profiles, but on a more extreme scale.

The end results of Kawamoto *et al.*, (2001) highlighted the effectiveness of implementing power management. With NPM, the annual total office energy consumption was 97TWh and with maximum PM including night switch off the

consumption was 55TWh, a difference of 43%. The results indicated that the key areas in energy savings were copiers, displays (monitors) and laser printers, followed closely by terminals (PCs). This can be confirmed by referencing the research carried out by Kawamoto *et al.*, (2004), Mungwititkul *et al.*, (1997) and Koomey *et al.*, (1995).

2.9.3 Power Management in Schools

Section 2.9.1 discussed several energy saving measure, and power management options for equipment in offices. The majority of equipment, including PC's, monitors and printer/copiers can be found in schools, though generally not to the same extent. Computers can be found in schools, usually small numbers in classrooms, and larger quantities in dedicated lesson rooms, such as computer studies or technological studies. There are other technologies such as over head projectors (OHP), computer projectors and interactive white boards that are now becoming common within schools. Additionally there are potential energy savings found in the heating systems, lighting and whether or not the school has a swimming pool. This section discusses possible energy saving measures within schools.

2.9.3.1 Energy Savings in Schools

There have been several documents published by the Carbon Trust, aimed at reducing energy consumption and promoting energy efficiency in schools. These documents include; The Good Practice Guide – Saving Energy a Whole School Approach (Carbontrust, (2008)), Schools – Learning to Improve Energy Efficiency (Carbontrust, (2010a)), A Whole School Approach (Carbontrust, (2010c)), and The Energy Consumption Guide 73 - Saving Energy in Schools (Carbontrust, (1999)). It should be noted that the publication CTV037 is a managerial version of the Good Practice Guide. Additionally, the Energy Consumption Guide 73 (ECG73) is similar to the Energy Consumption Guide 19 (ECG019), but is aimed it schools instead of offices.

The various reports discuss energy saving in schools with changing degrees of details. From the guides there are several key areas where there could be potential energy savings. These include; heating/cooling, building materials, lighting, equipment, and swimming pools.

In terms of heating, this can be ideally broken down into fossil fuel and electric heating. It is assumed in both the Good Practice Guide and the Energy Consumption Guide that the space heating is fossil fuel based, and not electric. Most likely the majority of the school building stock will utilise fossil fuel heating. From Figure 11, the

heating can account for 58% of total energy consumption, accounted for 45% of total energy costs (Carbontrust, (2010a)). Any savings within this sector could result in large energy and financial savings.

There are many options available to reduce the heating demand of a school. The simple options include ensuring that thermostats are serviceable and set at the right setting. Ideally removing the occupant's interaction with the heating thermostats would remove the need to check them. The Whole School Approach guide (Carbontrust, (2008)) stated that the false belief that putting the thermostat up to maximum will not increase the warm up time has to be removed from the occupants. Other initiatives include ensuring the pipe work is properly insulated, and that the boiler is regularly serviced (can provide a 10% energy saving). One of the most obvious energy reduction measures is to ensure that the heating is only used when it is needed. Ideally the heating should come on just as the school is being occupied, and the building should start cooling as the occupants leave.

A more extreme form of heating energy reduction is to upgrade the boilers for newer energy efficient boilers and even change the type of fuel burned, as outlined in the Carbon Trust's publication Low Temperature Hot Water Boilers Carbontrust, (2006a). The heating controls (boiler switch on times, temperature sensors) have to be checked as well. Newer heating controls incorporating sensors that can compensate/adjust the heating based on localised weather are becoming popular. One case example outlined in Carbontrust, (2009a) was that a school invested in new heating control, replacing the ones fitted in 1977. The result was a 21% saving on the heating demand.

In terms of building materials and components, there are several solutions available. Installing double glazing and blinds can help reduce drafts and overheating, that would normally increase heating and cooling respectively. Additionally, installing more insulation into the walls and roof can reduce the heating load.

The lighting demand can account for over 8% of total energy for a 'typical' school, which in turn relates to over 20% of the total energy costs (Carbontrust, (2009a)). Similarly with the heating saving measure, there are a number of easily implemented initiatives. These include switching lighting off when rooms/areas are not in use, replace failing light bulbs/tubes and placing 'Switch Off' stickers near light switches. Also ensuring that artificial lighting is not being used when natural light levels are high enough or lighting being used whilst curtains/blinds are closed, can further reduce lighting demand.

Further initiatives include installing occupancy and light level sensors to control the lighting, and/or ensuring current lighting controls are serviceable. Other more costly solutions involve replacing the lighting with more efficient technologies. Classroom lighting can be replaced with compact florescent lighting (CFL), which offers 75% energy savings against older incandescent bulbs. Large open areas, normally flood-lit with filament/tungsten halogen lights can be replaced with metal halide 65%-75% savings. Ceiling mounted florescent lighting, usually found in classrooms and halls, can be replaced with fittings that use reflectors and louvers allowing a 30-45% energy saving.

The discussed initiatives could substantially lower the energy consumption, hence cost, associated with lighting.

As previously stated, several pieces of equipment found in schools can be found in offices, such as PCs, printers and copiers. The same energy efficient measures discussed in section 2.9 can be applied to the schools. The main difference is that the consumption associated with the equipment usage is different between the two types of buildings. Even within schools, this proportion can be different, such as number of computers in a primary school in comparison with a secondary school. Equipment can account for around 3% of a schools total energy, though only 1% is related to what is classed as office equipment (Carbontrust, (2008)).

Initiatives including upgrading the computers, ensuring equipment is turned off and that equipment standby features are enabled can reduce the power demand of the equipment sector. Switching of the PCs monitor when not in use can save up to 60% of total energy consumption of the PC. One initiative that is not mentioned in section 2.9, is ensuring that purchased equipment does not over exceed the requirements. Having a powerful, high power processor PC with a large monitor would be considered an excess if its primary role was to check emails, or run basic programs.

An example of equipment energy saving was provided in the “Schools - Learning to Improve Energy Efficiency” publication (Carbontrust, (2010a)). Fume cupboards are usually found in science labs (not applicable to primary schools), and are used to extract potentially harmful fumes away from an experiment. A fume cupboard consists of an electrical extraction fan, that is fed cool air from the surroundings and extracts for the outside. One problem is that the surrounding warm air is taking, removing heat from the room. Fume cupboards can often be used as chemical stores, requiring constant fume extraction. By switching off a fume cupboard when not in use,

could reduce costs from over £750 per year to less than £200 per year (per fume cupboard Carbontrust, (2010a)).

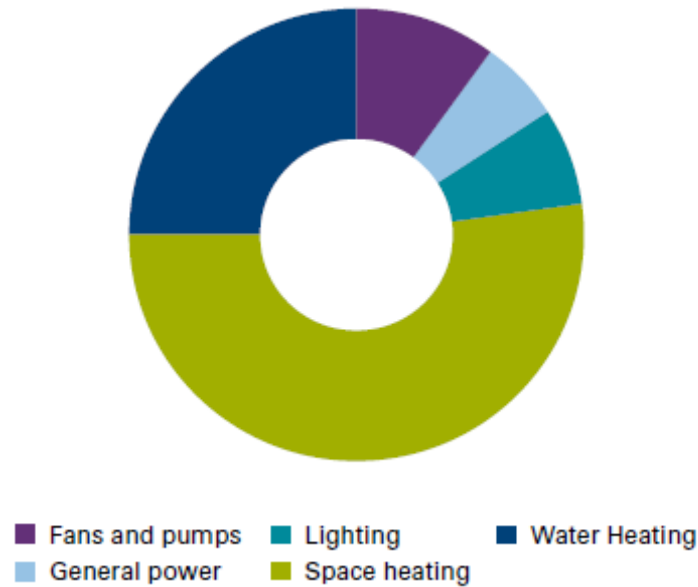


Figure 50 - Breakdown of Energy Use of an Outdoor pool, Carbontrust, (2006d)

The last key area for potential energy savings are swimming pools. Generally, primary schools will not have a swimming pool, and not all secondary schools have a swimming pool. The schools that have pools could halve several energy saving measures available. A pool for a typical 600 pupil school could cost around £7,500 a year to run (Carbontrust, (2009a)). Any savings on the cost of running a pool would be very beneficial. A breakdown of pool energy consumption is shown in Figure 50. It should be noted that these energy savings are related to UK schools.

The first measure is ensuring that the pool has a serviceable cover. As stated in Carbontrust, (2009a), a school pool has to be heated to a set temperature 24 hours a day. The pool itself may only be used for several hours in the day, hence heating an unused pool may seem wasteful. A pool cover can reduce heat loss, and hence has the potential for saving 25% of total pool energy consumption, or 90% of night time energy consumption. The use of solar hot water system may further reduce the heating demand of a pool.

The heating and ventilation of the pool room is also important to consider, and represents over half of the energy associated with a swimming pool (Carbontrust, (2009a)). The pool room has to be heated to 1°C above the pool temperature (which is generally around 28°C). This creates a large heating loss, requiring constant ventilation to maintain the working temperature. There are many options available to reduce the pool room heating demand. The first is to upgrade the ventilation and humidity

controls. According to “How to Implement Energy Efficient Swimming Pool Ventilation, Carbontrust, (2009b), basic pool controls consist of a manually controlled single speed fan unit. This could be replaced with multi speed fans, variable speed controllers and humidity controlled fans. This would result in the ventilation system only being used when it was required. Another possible solution is introducing a heat recovery system. This takes the wasted heat from the pool and uses it to preheat incoming fresh air.

There have been many successful examples of reducing the energy demand of a swimming pool. One school introduced humidity and temperature sensors in the pool and allowed the pool room conditions to be carefully controlled. This resulted in a £7,000 a year saving, offsetting the initial costs in only two years. A second school incorporated a new pool cover, had temperature and humidity controls, and incorporated smaller boilers to heat the pool (instead of one large boiler). This resulted in the school saving over £14,700 (against the original running cost of £18,100), and had a payback period of over 2 years (Robinson, (2003)).

This section discussed several energy saving and energy efficient measures that can be readily applied to either new schools or be included in the retrofit of older schools. Several discussed measures are simple to apply, and involve no financial investment. These include switching off lights and computers. Other measures involved replacing equipment, such as boilers, lighting and controls that require considerable investment. Although the initial investment is high, as the examples have demonstrated, the payback periods can be relatively short.

2.10 Energy Efficiency

Energy conservation is extremely important for any building because it can offer both carbon and financial savings. There have been several investigations carried out to determine possible energy saving solutions for potential use in buildings.

Chen *et al.*, (2006) investigated the impacts of potential energy saving systems on an existing building. Chen *et al.*, (2006) set out to determine the end effect of applying energy conservation measure (ECMs) on a commercial building in Shanghai.

The first part of the investigation was aimed at determining what the offices' current energy consumption was. This was achieved by first recording basic details of the building. The initial building data included; a) the total floor area, b) number of stories, c) age and d) key services and ratings. The initial inspection revealed that the building was over ten years old, has forty-one floors, a floor space of 67000m²

(although the AC unit chills only 58500m²) and incorporated three centrifugal chillers and three steam boilers. Once these results were recorded, Chen *et al.*, (2006) investigated the thermal properties of the buildings and recorded the thermal transfer coefficients, or U-values, for several key areas. These areas include a) interior walls, b) exterior walls, c) floor, d) ground, e) ceiling, f) the roof, and g) the windows. The last parameter measured by Chen *et al.*, (2006), was the HVAC system. Measurements such as HVAC type, temperature settings and efficiency were all noted.

Chen *et al.*, (2006) discussed that the recorded data was fed into an energy simulation package to calculate the total energy consumption of the studied building. The simulation concluded that the building consumed 9,210,000kWh/yr, or alternatively 9.21GWh/yr. With this base energy consumption value established, Chen *et al.*, (2006) proceeded to discuss the ECMs adopted in the paper. The six chosen ECMs were as follows; a) optimising chiller operation, b) variable flow pump control, c) more efficient fans, d) replace one cooling tower, e) replacing two cooling towers and f) reduce the lighting intensity within the building. A seventh ECM was also mentioned by Chen *et al.*, (2006) which was all six of the previous ECMs combined, known as the integrated ECM. The energy simulation was modified to incorporate the different ECMs and the resulting energy consumption for each individual ECM was recorded. The end result was a 6.1% energy saving from the integrated ECM with a potential payback time of 3.6 years.

Several interesting points were highlighted by the work undertaken by Chen *et al.*, (2006). The first is that it demonstrated potential energy savings, hence financial savings, can be achieved if ECMs are incorporated into a building. The second was that the results indicated that reducing the lighting intensity was the most effective ECM in terms of reducing energy consumption. The downside is that very little information is given regarding the ECM. Details such as how the lighting intensity was reduced, or how were the chillers optimised were never stated. Another company wishing to adopt similar ECMs would find it difficult to replicate the results stated in Chen *et al.*, (2006). It should be noted that the study appears to be more of a feasibility study rather than an energy reduction methodology.

Similar work to Chen *et al.*, (2006) was undertaken by Junnila, (2007), the difference being that it focused on electrical equipment and buildings services. One aim set out by the work undertaken by Junnila, (2007) was to determine the effects that end-users, or workers, have on energy conservation. Junnila, (2007) started by stating that any benefit associated with energy conservation ideas, are generally overtaken with

initial investments cost. This results in several profitable energy saving schemes not being adopted by companies. An interesting point made in Junnila, (2007) is that the majority of ECMs are technology based and not behaviour based. The main drive behind Junnila, (2007) is to show that a combination of both behavioural and technological measures can provide the best energy saving measures.

The investigation studied four buildings, one from Denmark, Sweden, Finland and Norway. The chosen buildings belonged to the banking industries, and had sizes ranging from 160,000m² to 270,000m². An initial inspection of the building, similar to Chen *et al.*, (2006) was undertaken to discover; a) the total floor space, b) current level of energy consumption (based on energy bills), c) equipment lists, d) lighting details, and e) the equipment and lighting consumption.

The inspection provided base energy consumption values for the equipment and lighting in each of the studied buildings. The normalised energy consumption for equipment and lighting ranged from 13-27kWh/m² and 35-39kWh/m² respectively. Junnila, (2007), discussed the ECMs or ‘actions’ adopted in the study. The actions are broken into two classes; office equipment actions and lighting actions. The six office equipment actions were; a) shutting down PCs at night times, b) enabling power save functions on PCs, c) replacing all monitors with LCD panels, d) changing PCs to ‘EnergyStar’ approved PCs, e) replacing PCs with laptops and finally f) disconnecting PCs at night. Actions (a) and (e) appear to be identical; however disconnecting the PCs can avoid any off-state consumption. The three lighting actions were; a) turning the lights off when the rooms or the building is vacant, b) turning the lights off when there is adequate daylight and c) only using the lights when they are needed. Several of the actions suggested in Junnila, (2007) could be classed as common sense, but many companies still fail to adopt these simple measures.

To calculate the impact of each action Junnila, (2007) discussed that an energy calculation method was adopted. Although this method is not actually discussed, Junnila, (2007) stated that it is a method developed by the Lawrence Berkley National Laboratory (LBNL). The calculation involved inputting operational hours, low power usage, off-state usage, number of equipment and other important factors. The resulting consumption of each action were calculated and presented in Figure 51. The figure highlights each scenario for reducing the office equipment energy use. The table also highlights that each scenario is the same as the previous scenario, but with an additional action. Implementation of scenario 6 (or all six office equipment actions combined) provided the greatest energy savings. Building A’s consumption fell from 27kWh/m² to

5kWh/m². The lighting actions table demonstrated that with all three lighting actions adopted, the average of 10kWh/m² could be saved. Junnila, (2007) concluded that if all the lighting and office equipment actions were adopted, the average electricity savings for lighting and equipment could be between 40-50%, or 20% of total energy consumption.

Energy conservation scenarios	Electricity consumption [kWh/m ²]			
	Case A	Case B	Case C	Case D
Base case	27	14	30	13
Scenario 1 (O1)	22	14	24	13
Scenario 2 (O1 + 2)	13	9	14	8
Scenario 3 (O1 + 2 + 3)	10	8	13	7
Scenario 4 (O1 + 2 + 3 + 4)	8	6	13	5
Scenario 5 (O1 + 2 + 3 + 4 + 5)	6	5	11	4
Scenario 6 (O1 + 2 + 3 + 4 + 5 + 6)	5	4	10	3

Figure 51 - Table of ECMs Junnila, (2007)

The research carried out by Junnila, (2007) provided a greater understanding on lighting and equipment based ECMs, and discussed the ECMs in greater detail when compared with Chen *et al.*, (2006). There is one issue with the scenarios described in Junnila, (2007). The last scenarios (6 and 3) involve applying all the actions to the building. It appears to be infeasible to replace the monitors with LCD screens, applying the energy saving controls and replacing the PCs with laptops at the same time. Similarly light action (c) is almost the same as (a) and (b), hence scenario 3 would be doing the same actions twice, which is impossible. Apart from these issues, the article successfully highlighted that the actions described were simple to implement and that not all involved investment. The actions are also applicable to several types of buildings, not just offices.

In contrast to Chen *et al.*, (2006) and Junnila, (2007) thermal energy saving measures were investigated by Dimoudi *et al.*, (2009). The research investigated nine school buildings in Greece that ranged in size, age and construction. Key building data was collected including construction type, current insulation, floor plan and energy consumption. The specific heating energy consumption ranged from 95.8kWh/m²/yr to 150.3kWh/m²/yr, with a mean value of 123.3kWh/m²/yr. The graph, see Figure 52, shows the heating consumption for each of the studied schools. The top two largest energy consuming schools are also the schools without any thermal insulation. This reinforces the point of increasing insulation in schools in order to reduce energy consumption

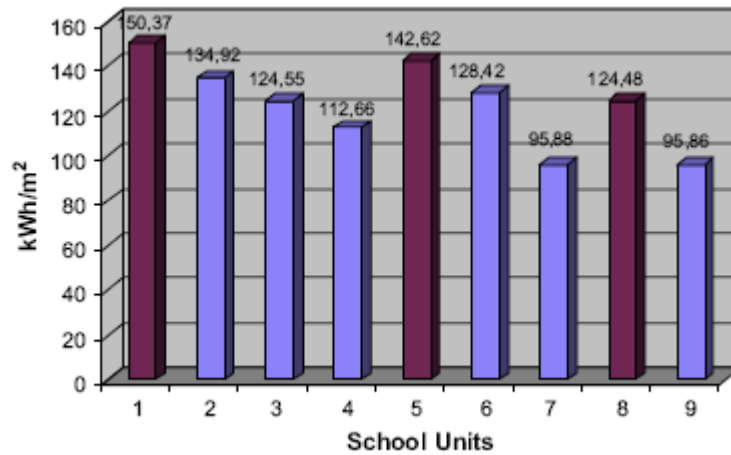


Figure 52 - Heating Consumption of schools Dimoudi *et al.*, (2009)

The aim of the investigation was to lower the energy consumption associated with heating using ECMs. Dimoudi *et al.*, (2009) justifies this study by demonstrating that the energy used for heating in schools is greater than the electricity consumption. In the nine schools, the heating (diesel oil) accounted for 87% to 92% of total energy consumption. Dimoudi *et al.*, (2009) produced six hypothetical building models based on the collected data and results. The six buildings each had the same thermal properties however their classroom opening orientations were different. Dimoudi *et al.*, (2009), proposed several thermal ECMs and divided them into two separate groups; heating period and cooling period. Considering both heating and cooling periods in the study is an interesting idea, because it could be assumed that savings could be found in both groups.

There were seven heating period ECMs or as Dimoudi *et al.*, (2009) defined them, ‘scenarios’. These are as follows; a) existing condition, b) insulation of support frame, c) increase in wall insulation, d) movable shading devices, e) additional top windows, f) decrease air permeability of opening and g) improving the thermal characteristics of the windows. The seven cooling period scenarios are as follows; a) existing condition, b) insulation of support frame, c) increase of wall insulation, d) length increase of shading device, e) ceiling fans, f) night ventilation, and g) night ventilation plus insulation of support structure. In both groups, the ‘existing conditioning’ scenario was the base value and was used for comparison.

Each of the discussed ECMs was applied to a model of the studied buildings and the subsequent results were recorded. For the heating period the most successful scenario was using insulation the support frame. This resulted in energy savings of over 13% in each of the 6 case buildings. Additionally, an interesting discovery was made in during the simulation stage. By adopting top windows, or scenario (e), the buildings

consumed more power (4-5% more). If each of the six scenarios were applied to the buildings, minus scenario (e), an average of 27% of energy could be saved. This value, however, is based on the assumption that all the scenarios can be applied together, and that no contradictions exist (unlike Junnila, (2007)).

For the cold period the most successful scenario was night ventilation and support structure insulation with an impressive average energy saving of 99.3%. The second most effective scenario was using night ventilation only, which had an average energy saving of 99.2%. All six scenarios cannot be applied to the buildings due to scenario (g) is an adaptation to scenario (f). Further work would be needed to investigate what would happen in a real building if all the discussed scenarios were adopted.

The research finished by Dimoudi *et al.*, (2009) discussed thermal measures for reducing energy consumptions. It offered a different angle for energy saving that could not only be applied to schools in Greece, but a variety of buildings in the UK.

2.11 Overall Literature Review

The literature review highlighted that global energy consumption is continually increasing, and a significant proportion is associated with the non-domestic sector. Without any intervention, non-domestic energy consumption could outstrip supply. Possible energy reduction (both in terms of power and fossil fuel) can be achieved by comparing known energy consumption against predetermined benchmarks. However, current published benchmarks were identified to have a limited scope, lacking detail on different building categories, construction age, or how the seasons impacted on the consumption of a building. The literature review determined that differences exist in energy consumption between different climate zones (tropical, non-tropical), and hence differences existed between the seasons (winter and summer).

The literature review determined that by monitoring the power demand (and thermal demand) of a building can have several benefits, both in terms of energy saving and financial savings. It was also established that monitoring a buildings energy demand at a finer time resolution (greater than annual consumption) can highlight potential wastage as well as indicate trends/patterns of energy usage within the buildings. Additionally, the methodology used to capture this energy data was also detailed, with NILM being identified as the most suitable and least likely to cause any issues to studied buildings. Lastly, the literature review highlighted that there was limited information/results of energy demand analysis at a half hourly time resolution.

In response to the problems and issues discovered in the literature review, several areas could add to this research sector. Analysing the power demand (and thermal demand) profiles for a wide range of buildings could determine if any trends in energy demand was identifiable. If such trends did exist, these could be used to predict power/thermal demand of a building and hence predict building and sector energy consumption. Additionally, this prediction data could be used to update current published energy performance benchmarks and introduce other identified influencing factors, such as building age, size, use and season/climate.

Chapter 3 EQUIPMENT AND METHODOLOGY

The aim of this research project is to develop a predictive model that will generate typical power demand profiles for various building types. The predictive profiles are derived from the analysis of a database created from various energy consumption data provided by several local authorities in the east of Scotland. Three main categories of data were used to construct the database and hence the predictive model for power demand profiles. These were electricity, thermal and weather. Each type of data and the means of collecting will be discussed in turn.

3.1 Half Hourly Electrical Data

The primary energy data used in this research project was electricity data. Several options existed for the collection of this data. The first option is using special monitoring equipment that measures the energy consumed within a building and provides a record of the energy used. This approach can be further sub-divided into two categories; intrusive and non-intrusive monitoring. An intrusive approach would involve interrupting the main power supply of the building to insert the monitoring equipment. As the name implies, this approach would cause disruption to the building's power supply, the length of disruption being dependent on the period of time that it would take to insert the monitoring devices. A more significant issue with this approach is that a building system specialist would have to install the equipment due to the complex power systems involved and the voltage of the electricity supplied to the building (advantages and disadvantages of NILM can be found in Section 2.7).

In contrast, a non-intrusive approach does not require the power supply being interrupted, as the system uses special sensors that are clamped round the power lines, instead of being inserted into the power lines. Non-intrusive systems have the advantage of lower installation time and have a lower installation impact on the studied building.

The decision was taken, that due to the disadvantages associated with an intrusive approach and for health and safety reasons, a non-intrusive approach would be taken to obtain electrical usage data from selected buildings. As mentioned previously the key advantage of this approach is that the monitors can be easily set up/installed with minimal impact on the building. A key criterion for the chosen equipment is that it should be able to record energy usage with a low error rate to ensure accuracy of the

data. Originally several voltage monitors were selected as suitable for obtaining and recording the electricity data.

Originally, the decision was taken to collect electrical power demand data by purchasing and implementing three-phase monitors (three-phase monitors are essential for larger buildings). Suitable equipment was sourced from Wessex Power. The selected equipment, the EnergyPro 3 Phase Data-logger, had the ability of monitoring the power demand at varying time resolutions, had a high accuracy ($\pm 0.5\%$) and utilised either flex or clip-on current transformers. A key disadvantage of this monitor is that each unit cost £2,095 (Wessex Power, (2005)). To successfully monitor a wide selection of buildings, several monitoring systems would have to be purchased, resulting in substantial project costs. The other option would be to buy one or two monitoring systems, and then implement a shorter monitoring time on each building, or increase the overall monitoring stage of the project (although this could take several years). If power data-loggers were to be used, a balance would need to be found between number of monitored/studied buildings, and data collection time.

There are three sources of electrical data available to monitor; main feed, distribution board and appliance. Monitoring the main power feed into a building (at the meter side), requires only one three-phase monitor, and would record the building's total power demand. The recorded data will provide an insight into the total energy demand of the building, and can indicate (if enough temporal resolution is used) the total daily power demand profiles. Therefore this approach is of value even if the data has to be interpreted to determine where energy/power is being used, and what equipment is contributing to the total power demand. Interpreting the data requires several assumptions and therefore is open to subjective interpretation with decisions being made by the judgement of the user. One approach to overcome this inherent disadvantage of using data from main electricity meters is to monitor electricity demand through the use of electricity distribution boards throughout the entire building.

Monitoring the distribution boards allows detailed electrical data to be collected and analysed. The distribution boards meter electricity into different sections or equipment in a building and these divisions can vary between different buildings. It is therefore possible to separate and monitor electricity demand at each floor of a building or by different electrical systems such as lighting and I.T systems. The main advantage of monitoring the distribution boards is that a detailed view of electrical usage can be gained over the total electrical power demand. One disadvantage is that to monitor each distribution board requires a large number of monitoring systems. Similarly with

monitoring the total electrical demand, the equipment required to monitor electrical distribution boards are expensive. There are several organisations and companies that offer a detailed monitoring service, such as NoWatt. NoWatt install energy monitors on each distribution board, and all information is sent to an online server. The data is accessible via the internet for viewing and analysis (NoWatt, (2010)). Key advantages of this service is that all monitoring equipment is provided, the data is automatically downloaded to the online server (negating any need for building owners to manually download the data), and data can be accessed at anytime and anywhere.

Lastly, appliance monitoring (see section 2.7) involves placing monitors (usually current transformers) on every appliance or piece of equipment that demands power. The key advantage of this is that a very detailed view of how and where power is used in a building can be generated. This removes the requirement of disaggregating the data into components (lighting, IT, heating, etc) based on assumptions. Key disadvantages of this approach include a large number of energy monitors are required to record the power demand of each appliance. The resulting database would be extremely large (depending on number of appliances, recording time, and monitoring length) that could result in a long data processing stage. Potentially, monitoring companies such as NoWatt could appliance monitor, however this solution would still entail significant numbers of energy monitors.

Due to the scope of the project, it was decided that main feed power demand data was sufficient. The ethos of this project was determining trends in power demand between buildings and building types. More detailed power demand data (distribution board data, or appliance data) can be useful in determining what systems resulted in certain demand patterns, or useful in determining similarities between buildings at an appliance level. However, for this project, this level of detail is not necessary, as key building traits or general equipment (swimming pool, heating type, etc) can be accounted for when analysing total building power demand.

An alternative source of electrical data was discovered that negated the requirement for monitoring equipment. The power suppliers of Edinburgh City Council, as well as other sources used in this project, monitor and record the electrical use in each of their buildings. This results in large electrical databases for a wide range of buildings. The Council allowed access to the database that contains all the Council buildings. This data covers 2008-2010 and in a thirty minute time resolution. There are several advantages of using this pre-recorded electrical data. The first is that expensive electrical monitors are no longer needed, and considerable project expenses can be

reduced. The second advantage of using this data is that the data has already been collected and the data gathering stage is subsequently reduced. The last advantage with this source of data is that there is the possibility of collected/downloading previous annual data, allowing the creation of a much larger database. In addition, one company provided distribution board power data for one of their schools. The school was being monitored by NoWatt services to determine why the school had greater than predicted energy consumption. This data was provided with additional distribution board descriptions so that a breakdown of what systems were attached to each board could be known.

3.2 Thermal Data

Although the primary interest of this research project was on electricity consumption, thermal data was also considered as part of the supplied data. As with electrical data, thermal data can be monitored using either intrusive or non-intrusive technologies, with similar advantages/disadvantages as described previously. However, the collection of thermal data using an intrusive approach opens the possibility of causing a gas leak when installing monitors raising health and safety concerns. As the advantages/disadvantages of using a non-invasive approach to monitoring thermal data outweighed the advantages/disadvantages of using an intrusive approach the non-invasive approach was chosen for this research project.

Ideally monitoring systems that are solely designed to monitor and record gas usage should be purchased. However, locating thermal monitoring systems that matched this specification proved difficult. As an alternative, a monitoring system that detected the flow of water was purchased and a thermal demand methodology developed.

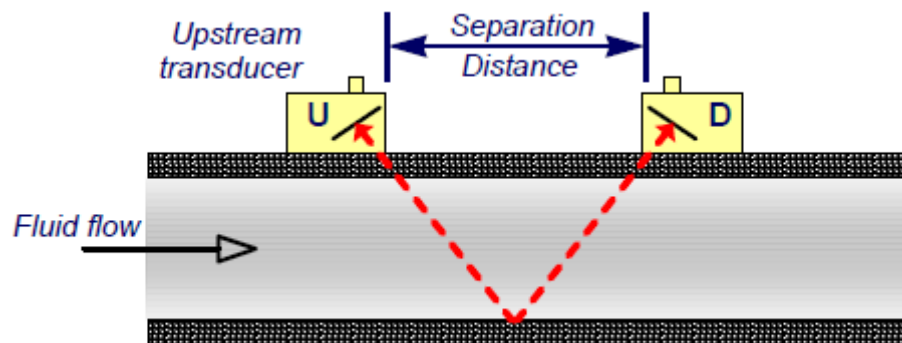


Figure 53 - Non-Intrusive Sensor Methodology Micronics, (2009)

The non-intrusive monitoring system (Portaflow 3000) uses an ultrasonic clamp that is attached to the outside of the pipe in which thermal demand is to be monitored and this is illustrated in Figure 53. It should be noted that this system does not monitor the thermal demand (of the boiler) directly, however monitors the water flow through the boiler, which in turn can be used to calculate thermal demand. The clamp houses two ultrasonic transformers set at a certain distance apart. One transducer emits an ultrasonic wave that bounces off the opposite side of the pipe and is returned to the second transducer. The flow of gas/liquid in the pipe accelerates the wave slightly, and it is this difference that is used to calculate the speed of the liquid/gas. The monitoring system takes a second reading, but this time uses instead the second transformer to emit a wave against the flow of liquid/gas.

The speed of the second wave is slowed down slightly by the flow, and the difference is calculated. A key part of the set-up of the monitoring system is inputting the pipe details. This value is used in conjunction with the speed data to calculate a volume flow rate (m³/s, L/s, gallons/s). The main advantages of this system are that it can be set up to measure different time periods. Another advantage is that there are several different transformer clamps of various sizes that allow fitting of the monitoring system to a wide range of pipes.

The ultrasonic flow meters that were purchased were only capable of monitoring and recording the flow rate of water/liquids in a pipe. To enable the monitoring of gas usage or thermal demand from the building required manipulation of the output data. The first stage was to determine exactly what thermal energy was, and hence how it can be monitored. Thermal energy use is defined as the amount of energy used to provide heating comfort to a building. If the building uses a water based boiler system, as the majority of non-domestic and domestic buildings do, then the above definition of thermal energy can be modified as the amount of energy needed to heat water to gain the thermal comfort of the building. From this definition, Equation 4 can be constructed.

Equation 4 Thermal Energy

$$q = m * C_g(T_f - T_i)$$

Where q is the energy required

m is the mass of water

C_g is the specific heat capacity of water

T_f is the final temperature of water

T_i is the initial temperature of water

To determine the energy needed by the boilers to heat a building, the temperature of the water entering into the boiler system (T_i) and the temperature of the water exiting the boiler system (T_f) has to be determined. In order to measure these two variables, two temperature sensors (K-Type thermocouples) were purchased with the corresponding data loggers (QuadRTD 4 Channel Temperature data-loggers). Fortunately, a large proportion of heating systems use a common return pipe and a common outlet pipe. The common return pipe is a system feedback pipe that recycles the systems hot water, reducing the requirement for fresh water (hence reducing energy consumption). Additionally, the common return pipe can connect multiple boilers.

The advantage of having multiple boilers connected to a common return pipe is that only one monitoring system is required to provide the thermal data of T_f of the equation, thus placing a temperature sensor on the common return and common outlet pipe, allows both the initial temperature of the water entering the boiler and the final temperature of the water exiting the boiler(s) to be determined.

An overview of the setup of the temperature sensors is shown in Figure 54.

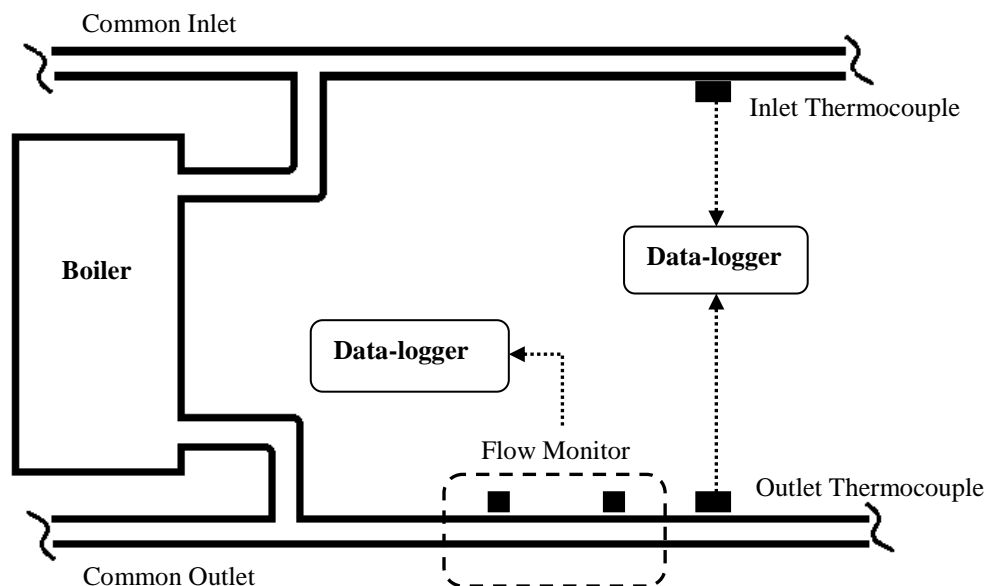


Figure 54 - Boiler Monitoring Set-up Overview

With the flow rate and temperatures determined, Equation 4 can be used to determine the energy required to heat the water. The equation had to be modified slightly to adjust for a flow rate, rather than a mass of water.

Table 4 - Monitored Pipe Dimensions

Pipe Diameter	Pipe Thickness	Lining	Pipe Material	Fluid	Resulting Separation Distance
225mm	8mm	None	Steel	Water	146.78mm

The key information relating to the boiler water outlet pipe was recorded and is presented in Table 4. Also included in the table is the sensor separation distance calculated by the PortaFlow 300 based on the specifications of the monitored pipe.

As with the electrical data, online gas meter data was also available for several buildings. The online data removed further project costs as expensive equipment was no longer required to obtain thermal usage data. However, the available online data represents total gas data collected from the main feed gas meter. This is not an issue for electricity data (in terms of using meter data), because this research project is focused on total electrical use. Conversely, this project is only interested in the gas usage of the boiler. Metered gas data will represent all gas usage, including primarily boilers, but can also include catering and lab gas usage. Although the gas boilers will be the largest consumer of the gas, caution should be used when analysing metered gas data.

3.3 Weather Data

Weather data is an important factor to consider when analysing building energy consumption data. By introducing different weather variables into the analysis, key trends between a building's energy use and surrounding micro climate can be determined. In order to accurately measure micro climate weather, weather monitoring stations were purchased and installed on two different buildings in Edinburgh. Ideally each monitored building should have its own monitoring station if an accurate and fair comparison between each building is to be made. However, the monitoring equipment was expensive and it was not feasible to purchase a weather station for each monitored building. In order to overcome this limitation, a detailed energy analysis was carried out on the two weather monitored buildings that were used as case studies.

The two weather monitors, Vantage Pro2 weather stations, were purchased and installed in two sample buildings. These monitors can record at different time intervals and record a wide range of variables. The systems were set up to record at a half hourly time period, to match the time interval of the energy data. One important feature of the Vantage Pro2 is that it is a wireless based system that can transmit data from the

monitor to a remote receiver. This removes the requirement for the data logger (or console) to be located at the weather station, and removes any wiring issues related to recording the weather data. The data logger can be placed within 100m of the weather station, although this range can be reduced by walls and ceilings.

The purchased monitoring station uses a long life battery, and integrated solar panel to allow a monitoring period of over two years without the need to replace the battery. The weather station has a monitor, essentially an LCD screen that is part of the storage data logger. The weather station can record, based on a half hourly recording interval, for up to eight weeks before the data logger's memory is full and the data downloaded. As mentioned previously, the weather station and monitor are linked together via a wireless connection removing the need to lay connecting cables and drilling holes in walls. The weather station was set to record the following parameters:

- Wind (direction, speed)
- Temperature (indoor, outdoor)
- Rain rate (set in mm/hour)
- Humidity (indoor, outdoor)
- Pressure
- Solar Irradiance

A solar sensor was also added to the standard weather station to monitor solar irradiance and solar energy. Additionally, other variables were calculated based on the data collected from the above weather variables. These other variables include; degree day (cooling/heating), wind chill, dew points, and maximum/minimum values of each primary variable. The weather station takes several readings a second, and then averages the values over the selected interval time period. The maximum and minimum values are also noted and outputted as high and low values, eg 'High_Temp' and 'Low_Temp'.

Another source of weather data was obtained for reference purposes. Airport weather data is readily available and can be downloaded from a variety of sources. This data can be used to either replace the need to buy expensive equipment, or to check the accuracy of the collected weather station data.

3.4 Establishing the database

The establishment of a database to contain the data, whilst at the same time making it easily accessible, is an extremely important aspect of this project. The key therefore is to successfully organise the collected data and present it in a set format that

can be interrogated, allow cross comparisons to be made within the database and allow subsequent output data easily exportable to other software programs if required. The databases established for the data obtained for electricity, thermal, and weather is discussed in turn. In addition the approach taken to “normalise” the data to make cross comparison across each data type will also be discussed.

3.4.1 Electricity

Organising the database for electricity was complex due to the abundance of data (in comparison to thermal data). This was due to the variety of formats and file size that this data was provided by the respective sources. The first stage in creating the database was to separate the data into the individual files for each building, as many councils provided a single file containing data from several buildings. Each building was given a unique identifier and all data related to a particular building was saved in its respective building file. This overall file for electricity therefore contained multiple identifiable buildings with all corresponding data contained within the respective building sub-file. Each file contained electricity data for the available years for which the councils collected and provided for the project. With the buildings separated into individual files, an appropriate format to database and store the data was required.

Councils sent electrical data in numerous formats including Microsoft Excel (.XLS), text files (.TXT.) and web based files. Excel files were considered the most appropriate as a result of the relative ease to which copy/paste could be undertaken, the in-built logic functions of the software and the graphical options that existed within Excel. The final consideration was the units that the electrical data would be expressed within the database. The provided data was in either power (kW) or actual meter data (kWh). It was decided to use kW, in recognition that this project was defining power demand profiles.

The generated building files included a time index in the columns (or x-axis) and the profile data in the rows (y-axis), *see appendix A for example of building file*. In addition, the different years of data (eg 2007, 2008, 2009) were separated into different tabs within each file. A simple review sheet was added, including total energy consumption per year, monthly consumption, average daily consumption and average power demand profiles. Each variable was calculated using the built-in ‘Sum’ and ‘Average’ functions within Excel.

Incorporating the data into Excel therefore resulted in an Excel database containing multiple building files. Although these files were not compiled into a single

database file, they were available in and easily identifiable file structure within the Excel electricity database.

3.4.2 Thermal Data

The database for the thermal data was not constructed in the same way as the database for electricity as outlined in section 3.4.1. This was due to the limited data available and provided by the various sources. Only five buildings had gas usage data available, and due to this limited amount of data it was not necessary to generate a separate database for this source of thermal energy. However, each building was given a unique identifier. Thermal data was provided as total gas usage by volume (m³) as opposed to being provided as energy in kWh. As discussed in Section 3.2, the provided thermal data represents all gas usage and is not restricted to simply boiler gas usage. The raw gas usage data required a degree of manipulation to make it possible for comparisons to be made with energy demand arising from the use of electricity. Thermal data was organised into three columns; date, time and gas usage. The data was transformed into a similar output as the power data, with each row representing a day, and the half hourly time indexes represented by a column.

For the actual recorded data (using the methodology outlined in Section 3.2), a separate file system was adopted. The monitoring method used within the respective building produced several output files including the pipe temperatures and the actual flow rate. Both the thermocouple data loggers and the flow monitor data logger produced different formats of output files. The data from each output file was copied and transferred into an Excel file. The generation of one file made it possible to easily calculate thermal demand using the corresponding temperature and gas flow data provide along with the gas usage data for the respective building. *See Appendix A for an example for thermal data.*

3.4.3 Weather Data

The weather data collected by the weather stations required additional formatting and processing in order to standardise this dataset. The monitoring stations saved the data in a format that could only be read by their respective in-house software. However, the weather station software had a built-in export function, allowing the user to export the collected weather data in a range of different formats. The export tool also allowed the user to select the output dates (or time period), weather variables outputted and the time resolution of the data. The data was exported and saved in the Excel

format. This made it possible to upload the exported file directly into the Excel database set up for the weather data.

The weather data was organised into monthly data for each of the two studied buildings. This resulted in only two files being compiled, each with twelve month tabs for each year. However, analysis of the datasets indicated that several data points (within the weather data) were missing for one of the studied buildings. This problem was related to signal quality issues, as it was subsequently discovered that the monitoring console had been switched off during the monitoring period. The missing values were replaced with corresponding data that matched either previous values or data recorded from previous days. The corresponding data used to ‘infill’ the missing data was created by plotting the data surrounding the missing data and using it for carry-forward analysis to compensate for the missing data. *See Appendix A for an example of the adjusted data.*

3.4.4 Normalisation Factors

An important requirement prior to comparing power demand across building types is to normalise the data to adjust the energy data to the different types of buildings used in this study. The variables of interest that had to be considered as part of a normalisation strategy were;

- Total floor area (m²)
- Occupancy (numbers of pupils/occupants)
- Building type
- Building usage
- Operational hours/open times
- Weekend usage?
- Year of construction
- Additional equipment (servers/swimming pools?)

The accuracy of the final conclusions will be dependent on the integrity and accuracy of the energy usage data provided by the respective sources. Any small discrepancies within the data could ultimately impact on the conclusions reached in this project. Therefore factors that could impact on the accuracy of the data and aid normalisation will be discussed.

3.5 Data Organisation and Formatting

In order to analyse the electrical demand data and produce the outputs and profiles discussed in section 3.4.1, a consistent methodology was required. Initially, data

analysis was carried out manually on individual buildings with subsequent cross comparison of one building against another. This approach was possible and if a change was made to the normalisation of a building, a re-analysis would be undertaken to examine the impact that this change had make between the buildings. One disadvantage of this approach is that it effectively limits the comparison between two building with multiple analysis required to define the impact on all buildings within the database. Thus, this is an acceptable approach when comparing a small number of buildings; however when comparing tens of buildings, this method was not efficient and involved a large processing time to undertake.

To overcome this issue, a FORTRAN based analysing program was designed¹ to remove the manual aspect of the data analysis. The program loads the building electricity data and following processing, outputs the results into separate files. The key advantage of using this approach is that the input files, normalised data and the output files can all be changed within the program. An over view of the program is demonstrated in Figure 55.

¹ Created By Dr S Patidar

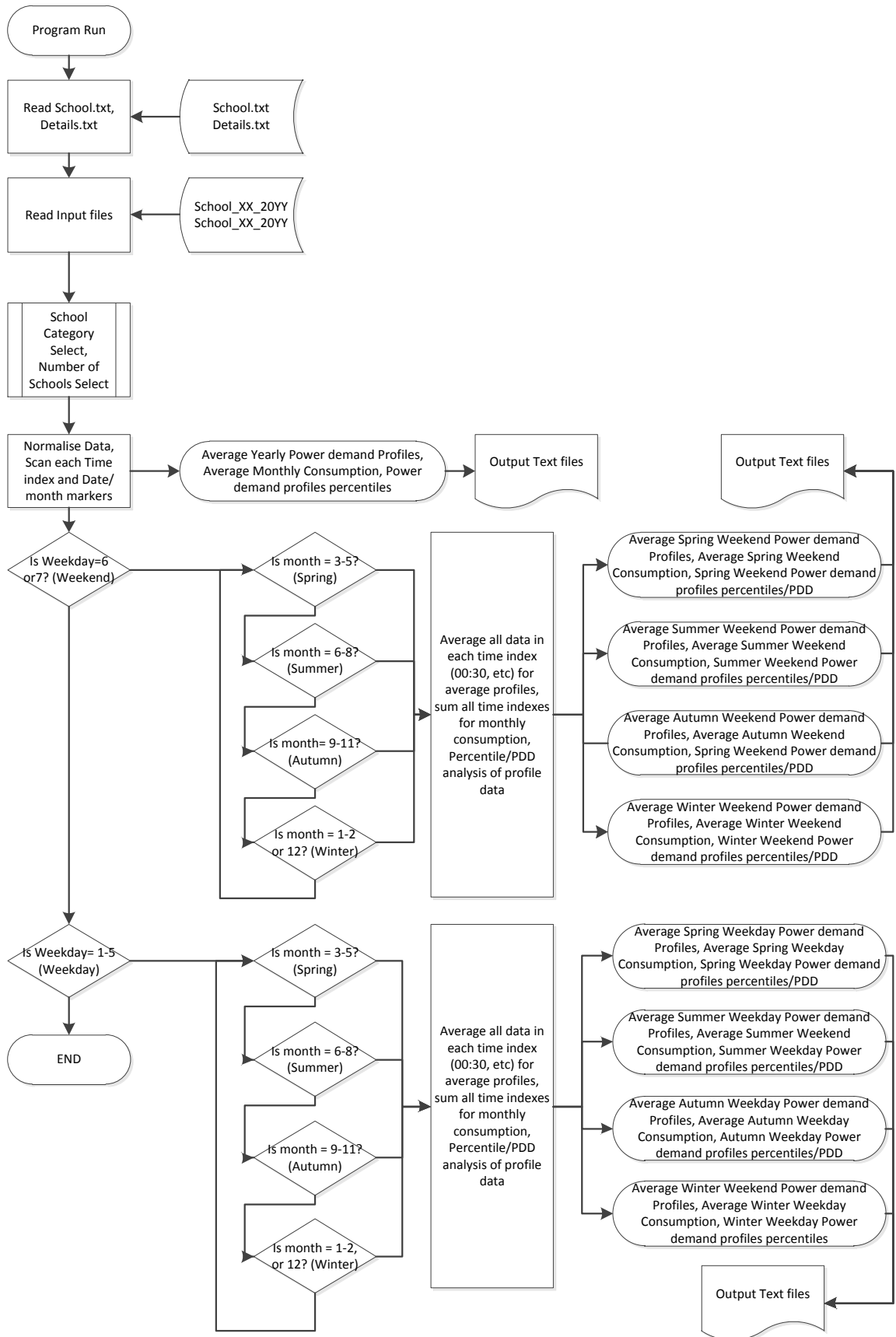


Figure 55 - FORTRAN Analysis Program Overview

Figure 55 demonstrates the key stages of the program and briefly highlights how the data is processed by the program. The program loads the data and the user can

select both the category (building type) and the normalisation factor(s), and the program then outputs the key results in separate files. The program has two main test sequences. The first is determining if the scanned data represents a weekday or weekend, and subsequently separates the inputted data into weekdays, weekends and both weekdays and weekends. The second test is applied out after the separation of the inputted data, and determines which season the data represents, and is subsequently applied to both the weekday and weekend data. Following each test, the process data is outputted to several output text files. A detailed explanation of the primary sections of the program and its outputs are discussed in the following sections. The program was designed primarily for the electrical data, due to the abundance of electrical data.

3.5.1 Data Input

The data input stage is the first stage of using the FORTRAN analysis program. The building power demand data must be entered in the correct format, and this format has to be consistent for all the schools. Thus in order to make the demand data compatible for the FORTRAN program, the demand data contained in Microsoft Excel files (EXL) was to preformatted into comma separated value (CSV) files. Converting the data from Excel to CSV format has several advantages. The first advantage is that the (CSV) files are very small, in comparison to the Excel equivalent. This is advantageous especially if the demand database increases in size (especially if there is a CSV file for each school and for each studied year). A second advantage is the FORTRAN based compiler can recognise the CSV files, and does not require the programme to convert them before analysing the data (allowing faster analysing). Each CSV file is given the format title of ‘School_20XX_ZZ’, where X represents the year, and ZZ represents the school number. *See Appendix A for an example of the data file.*

The analysis program loads an input file for each available year of data (‘School20YY, where ‘Y’ is the year). This input file lists each school data file, and the program uses this list to load each of the school data files. It is however, possible to define the number of schools that are analysed instead of processing all the school files. This is achieved by modifying the actual program code within the FORTRAN program.

3.5.2 Building Selection

The building selection section of the program allows the user to select the category of building that the program will analyse. The initial assumption made in this research project was that wide range of non-domestic buildings, including schools, offices, shops and others would form the database for analysis of power demand.

However, due to the lack of available data, as mentioned previously, the database was reduced to focus solely on schools. Within the school category, there are different classifications of schools (as discussed in Sections 2.5.2, 2.6.2). The user can modify the raw programming code to select how many schools and the type of schools to be analysed. Due to the analysing program containing a vast number of code lines, it was not possible for the program to be placed in the Appendices.

Future developments of the program will involve creating a Graphical User Interface (GUI) making the program more “user friendly”. In this proposed upgrade to the program, the user would be able to click the appropriate button, or use a drop down list to select the desired schools or types of school to be analysed. This would replace the need to modify the program code to make adjust the input, output or building selection. Alternatively, another input file could be created to allow the user to select which category of building/school and number of schools would be processed. The input file would also remove the requirement to modify the program code, and would be a more simplistic approach than creating a GUI.

3.5.3 Output Selection

The output selection part of the program allows the user to change how the data is presented in each of the output files, making it possible for the user to change how the data is to be normalised. The user selects the desired normalisation factor or output, and the analysis program loads an input file, ‘Details.txt’, which contains each school in the database, and the corresponding normalisation variables. Data from each school input file can be subsequently normalised with the correct factor and value. The program had four main output selections. The first output selection was to generate a normalised output with the output values presented in kilowatts (kW). The second output selection is normalising the data by floor area, in order to remove floor size factor when comparing different buildings. This results in the output files values having the unit’s kW/m² (or kWh/m² for daily consumption outputs). The third output selection is normalising by the data using the number of pupils and creating the output values units as kW/pupil (or kWh/pupil for daily consumption outputs). The last output selection option is normalising by both floor area and pupil number creating an output with values of kW/m²/pupil (or kWh/m²/pupil). The program can also generate define the impact of including other normalisation variables such as weather and total energy consumption. The program could be expanded to include other normalisation variables.

As mentioned above, normalisation of the data could include weather. The normalisation of energy demand to account for outdoor temperature, or solar irradiance could remove potential climate impact. As the majority of buildings in the databases are located within the east of Scotland normalisation of the data to account for weather may have little impact on the outcome. However, this would have to be considered if data was being compared from building located across Scotland, the UK or from outside UK.

3.5.4 Average Profiles

A key advantage of the program is that it can create average demand profiles for each school (and other non-domestic buildings) over a period of a year. The program loads one school data file at a time, and scans each value. The program sums every value at each time index (e.g. 09:00) and then divides by the number of summed values to create an average value for each time point. This process is repeated another forty-seven times (due to there being forty-eight half hourly values in one day), producing an average profile for the data file for one day. This averaging technique is then applied to the remaining schools, producing an average output file, with each average profile, and corresponding school number.

The developed program also generates two further average profile file outputs; a weekday profile, and a weekend profile. The program scans each day in each school to determine if the day falls on a weekday or a weekend day. This is accomplished by labelling each day in all the datasets with a number from 1-7. This is to represent a weekday number, where 1-5 represents a weekday, and 6 and 7 represent the weekend days. The program scans this label to determine the status of each day ie weekday or weekend. The subsequent average profile value is then added to either a weekend summation or a weekday summation for each time index. When repeated for all time indexes, two average profiles are created for each school. These are then outputted for each school and type of day.

The reason for creating the three different average profiles was to demonstrate the variability in each profile and to establish how important it was to select the appropriate data and to highlight potential issues associated with using average profiles.

3.5.5 Seasonal Averages Profiles

The seasonal averages were calculated in a similar way to the annual average profiles (section 3.5.4). However, instead of using the entire years worth of data in each school input file, the program first separates the data into the four different seasons

(spring, summer, autumn, winter) and calculates the average demand profiles for each season. The program uses a second data labelling system for each school input file to identify the different seasons. As well as using the weekday label to identify the nature of the school day (weekday/weekend), the program also scans a date identifier. However, the program cannot process normal date formats, e.g. dd/mm/yyyy or 26th September, as the program fails to identify any symbol that is not a number. In order to compensate for this, a simple numbering system was chosen. The month and date were given a number representing their place in the calendar, for example the 10th July would be represented by '710'. *See Appendix A for an example of the labelling system.*

Validation of the program was undertaken using several test conditions to confirm that the program would not fail using the generated date format and that filtering between dates was possible. Seasonal data was tied into the generated date formats. Following grouping of the data with the corresponding season, the program sums and averages the values producing average profiles, for each season, and for weekend days and weekdays.

3.5.6 Max/Min Values

The maximum and minimum values are important outputs when attempting to identify any trends in power demand across a specified year. The maximum daily value can be treated as the peak demand of the day, and the minimum as standby. Plotting both outputs demonstrates how the peak and baseload of the studied building varies throughout the year, and determines if there is (or not) a seasonal influence on power demand. The program takes each individual school data file and scans in the power data for each day contained within the school file. The program scans in the first value (i.e 00:00), and assigns this value as the peak and baseload value. The program compares the next value (00:30) with the peak/baseload values (or the 00:00 value), and determines if the number is smaller than the baseload, or larger than the peak. If the value is larger than the originally set peak demand, then the peak demand is replaced by the compared power demand (00:30). If the number is smaller than the baseload value, then the baseload value is replaced by the compared value. If the compared value is not smaller than the baseload value or alternatively is larger than the peak, the program ignores this value and proceeds on to the next time value (01:00).

This process repeats for all forty-eight time values in each day, for all 365 days in the year, and for each building in the database. The result is an output file with the maximum and minimum values for each day, and for each school.

3.5.7 *Monthly Averages*

The monthly averages represent the average daily energy consumption for each month for the respective school. The program initially scans in one building data file, followed by the power data value for each day. The program sums each power demand value at each day and divides the value by two (in order to adjust the half hourly power values in kWhs). This approach is then repeated for all the days in the example month (ie January would be represented by a '1' in the date stamp, hence all days with the '1' month stamp will be grouped together). The total monthly consumption is then divided by the number of days within that month, producing a daily average. This process is then repeated for the other months and buildings.

3.5.8 *Percentiles and Probability*

The program makes it possible to generate outputs to understand average demand patterns, average seasonal profiles and average monthly consumption. The program can also be used to simulate or determine the probability of a future power demand of a building taking into consideration the factors discussed previously. This ability to predict or define the probability of power demand is based on creating both percentile outputs and probability distribution data. The main advantage of creating this data is that it is beneficial for creating generic profiles, as it demonstrates the most likely power demand values for a given time.

The percentile and distribution calculations begin with a data organising loop. The percentile/distribution values are calculated for each of the time indexes (00:00, 00:30, etc). In order to achieve this, all the data relating to each time index (all the 00:00 power demand values in each day and for every school) are organised in an ascending order. Once completed, the program either calculates the percentile or the distribution of power demand data. The outputs from each equation (10th, 25th, 50th, 75th and 90th) are then stored for outputting. The probability distribution data uses the same organised data set as the percentiles. The probability distribution is determined by establishing the 'bin' size or number of sections the data will be divided into. As a default, the number of bins was selected to be five, although the user can edit the programming code and select any number of bins. The size of each bin or the range of data that falls in each section was calculated by the program using the following equation:

Equation 5 Bin Size Equation

$$\text{bin size} = \frac{\text{Maximum} - \text{minimum}}{\text{No of Bins}} + 1$$

The program calculates the probability for a value to fall within each of the bins, forming a probability distribution for each half hourly time index. This methodology was applied to the individual buildings, as well as groups, seasons and weekday/weekends.

3.5.9 Data Sorting Program

A second program was written² to organise the data into suitable output files following analysis by the initial FORTRAN program. Unlike this original analysis program, this code does not calculate any average profiles, or percentiles. Instead it loads the data files, separates the files into key categories, and then recompiles the data into several output files and new datasets (as used in the probability/percentile analysis). There are several key outputs from this program.

The first output file is a simple data compilation file, and consists of all the data from the school power data input files. This essentially copies all the data found in each individual school data file, and compiles it into one large file. An alternative method to accomplish this compiled output file would be to ‘copy and paste’ the data from the individual school data files into the one compiled file. However, one advantage of the new program is that incorporation of data into the program was automated. An advantage of the upgraded program is that any changes to the data set, such as errors, or a different output is required (i.e. normalised by floor or pupil), then the program can quickly modify the output files. The organising program used the same output selection as the original analysis program.

The next output identifies the weekend and weekday power profiles in each school input file, and then assigns the two types of day to an output file. This creates two new output files, a compilation of weekend days for all schools, and a compilation file for just weekdays for each school.

The last series of output files are for each season. Using the same seasonal identification process discussed in section 3.5.5, it was possible for the program to copy the profiles of each season in each school to individual seasonal output files. The seasonal compilations were applied to the weekend and weekday datasets, producing eight seasonal output files.

² Created by Dr S.Patidar

The compilation program was applied to each of the different years of data, different normalisation modes, and different school types. This resulted in 160 output files for the gathered database.

3.5.10 Program Validation

The creation of the FORTRAN analysis program was to allow the automatic and rapid analysis of large amounts of energy data (at a half hourly resolution) and to hence remove the requirement of manual analysis. However, the output data (in terms of the average profiles, monthly consumption, normalisation, etc) had to be accurate so that any conclusions gained from the program outputs were correct. In order to determine if the output files were free from errors, and represented the schools/buildings, the data contained within the output files had to be validated.

The validation involved comparing a sample of each output files against the manually calculated outputs. Before the creation of the analysing program, the initial database (consisting of twelve schools) were manually analysed to provide average power demand profiles (weekday, weekend), average seasonal demand profiles (weekday and weekend), monthly consumption and lastly percentiles. The data additionally underwent normalisation by floor area and (or) pupil numbers. These manually calculated profiles (and consumption values) were compared against the program outputs for each of the corresponding schools. The comparison revealed that the program was functioning correctly and hence the output files could be used the highest confidence level.

3.6 Data Cleaning

The data originally provided by the various councils and companies had to undergo various stages of ‘cleaning’ before being ready for analysis. Although the data did undergo cleaning this was prior to analysis in order to exclude bias into the analysis. The ethos of this research project is to determine a ‘typical’ demand profile and then hence be able to understand the reasons for the profile shape. Thus in order to obtain a “typical” demand profile it was necessary on occasions to remove “atypical” profiles from the datasets. However, this was kept to a minimum in order to try and maintain the integrity of the datasets. Both the electrical and thermal (monitored data only) were subjected to data cleaning prior to undertaking analysis on the datasets.

The extent of data cleaning for electricity and thermal data will be discussed in turn.

3.6.1 Electricity Data

Several factors were considered in relation to cleaning of electricity data. These include; a) zero data, b) unexpected profiles, c) holidays, d) half days and finally d) weather.

The first stage of data cleaning was to remove missing values or zero values. This type of error most likely relates to data collection issues or simple gaps within the datasets. Removal of missing or zero values is important for several reasons. The first is that any data files for the analysis program (as discussed in section 3.5.1) cannot be used as the program cannot compute blank values. Under these conditions, the program either crashed or produced several error messages when processing the data. Analysis of the data was only possible following removal of any blank data. Blank data also impacted on the plotting software selected to graph the output data. The software interpreted the data as missing values, and then automatically created random values to replace the missing points. This resulted in several non-consistent demand profiles, or alternatively large demand spikes occurring in the power profiles.

Finally, blank data also impacted on the generation of average power profiles. The program scans all data, creates a summed value, then divides by the total number of scanned values. The number of scanned values would include the zero values. Although technically this would be correct for an averaging methodology, it does generate an inaccurate demand profile. This was considered and as such the decision was made that any element that has a detrimental impact on the typical load profile would be removed.

A possible alternative to removing the data would be to recreate the lost or missing data. There are several methods available, and several advantages or disadvantages with each one (refer to section 2.8). An alternative approach would be to insert the last value i.e. use a carry-forward analysis approach.

The next issue to consider before processing the data is the removal of unexpected profiles. Unexpected profiles can be defined as any profile that does not comply with what would be considered the typical power demand of the building. An example of unexpected profiles is shown for school 7 (Figure 56). On initial inspection, there appears to be three separate profiles for this school. The first is the unchanging power demand, represented by the flat lines occurring between 0-10kW. The second is the power demand that occurs from 05:30 to 17:30, and resembles the shape of an arch. The last and more noticeable power demand profiles are the seven profiles that appear above the arch profiles.

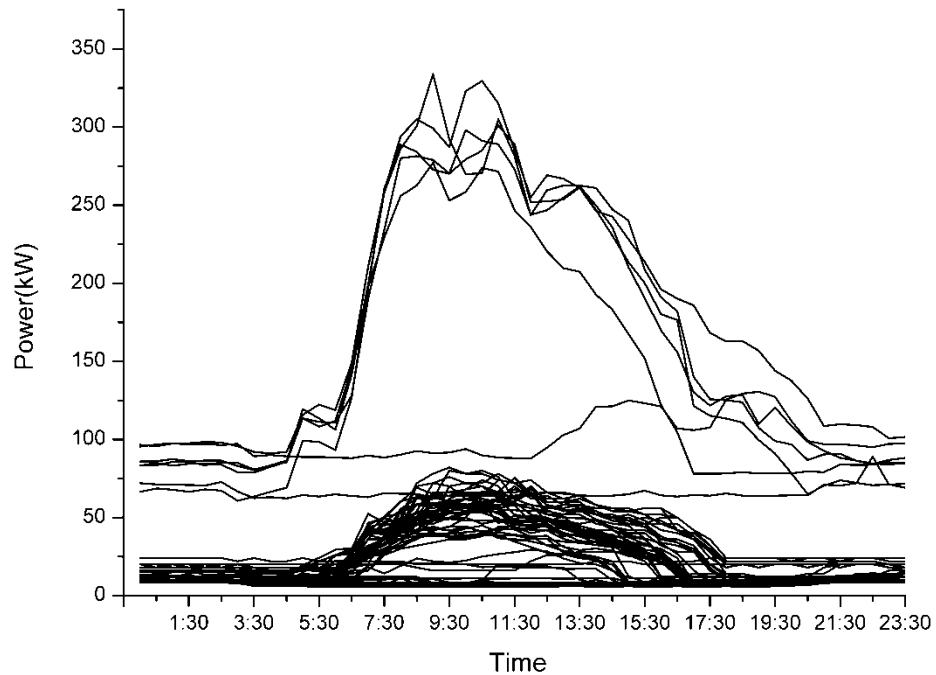


Figure 56 - Example of Unexpected Profiles

If the arch profiles are taken as the standard energy consumption, or the typical consumption, then the unchanging power demands (in the region of 5 to 25 kW) can be considered un-typical, and hence were removed. Although speculative, the unchanging demand profiles could be linked with weekend energy use, or days when the school is completely shut down, with little consumption bar equipment being on standby. The reason for the larger unchanging profiles (in the region of 60 to 100kW) is more difficult to explain. They may relate to data recording errors, or possible data errors at the power supplier's side. Visual inspection of outcome data therefore is useful in identifying profiles that may or may not be considered "atypical" and should be removed from subsequent analysis.

Removal of the "atypical" power demand curves should therefore give rise to more typical demand curves that can be used to predict future power demand based on a series of defined variables. The following sections describe further steps taken to derive typical power demand curves for the building studied in this research project.

The days that contributed to "atypical" profiles were removed from the dataset and the analysis performed again. As mentioned previously, the reason for the atypical profiles could relate to data collection issues or a failure in the metering device used to collect the information. They could also relate to how the data was collected. The data was collected by the power companies and provided to the respective school/building on request. It is unclear how this data was provided by the power supplier to the council

or building owner/tenant. If a wireless or wired (over phone line or modem) there could be transmit issues, causing random values being recorded.

Another factor that that can give rise to atypical profiles that will require subsequent data cleaning, is unaccounted school holidays. Unexpected profiles could therefore be associated with the school being closed as a result of unscheduled holidays. Events such as bad weather, as seen in the winter of 2010 could potentially close schools giving rise to a low or atypical power demand.

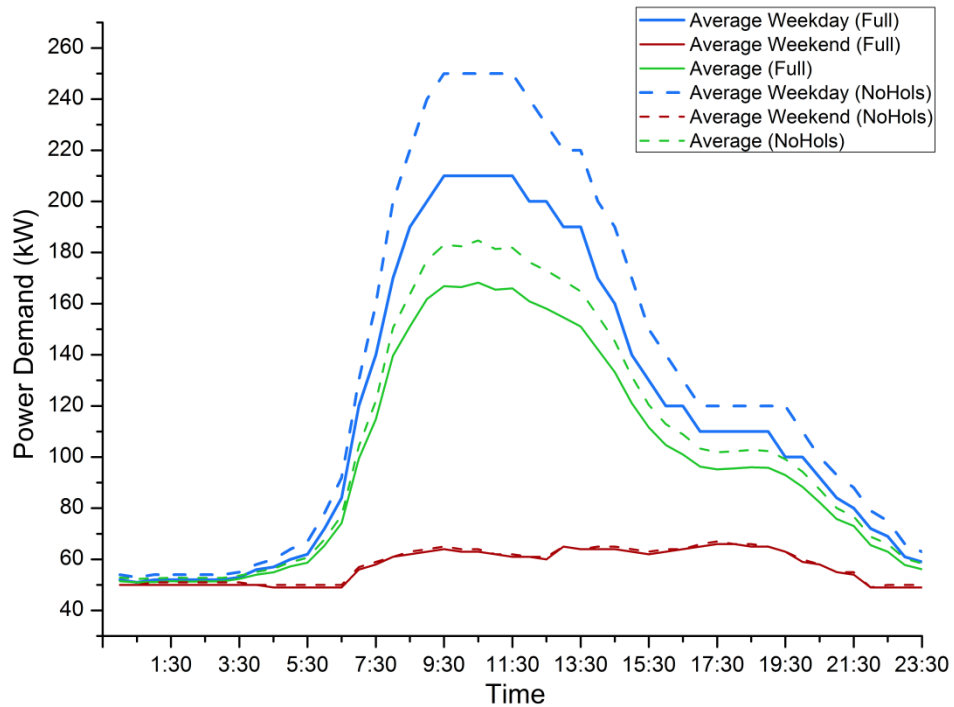


Figure 57 - Comparison between Holiday Dataset and Removed Holiday Dataset

Another factor that has to be considered in relation to data cleaning is school holidays. Schools are unlike other non-domestic buildings with regard to holidays. Generally offices will continue to run at normal or slightly reduced capacity regardless of whether staff are on holiday. Only when the buildings are shut for national holidays, such as bank holidays or Christmas, will the power demand be affected. Schools, conversely, have more scheduled holidays with a more pronounced negative impact on subsequent power demand during a holiday period.

Figure 57 highlights the difference between the average annual, weekday and weekend profiles, for school 25, for both the full database (shown by the solid lines), and the data set adjusted for school holidays (shown by the dashed line). There is an obvious variation between the two different datasets. This is evident with the average weekday profiles (shown by the blue lines). The peak demand of the full dataset is 210kW and the peak demand of the adjusted dataset is 250kW. This is an important

result, as the profile peaks are noticeably dissimilar. As discussed previously, the low daily consumption during the holidays is averaged with the normal working days, creating an average profile that represents all the days in a year. The larger peak demand in winter, where in the case of this example school can reach up to 300kW, is negated by the lower consumption during the holidays where peak demand can be as low as 60kW.

If the averages profiles (represented by the both green lines) are analysed, the shape of the demand profiles are very similar, however the peak demand and overall energy consumption differ. The average profile of the full dataset (with holidays) has a peak demand of 160kW, compared with the adjusted dataset that has a peak demand of 180kW. The demand profile that represents the full dataset appears to demand less power, and is attributed to several reasons. The first reason is that the low power demand in the holidays is being averaged out, as with the average working day profile. The second reason is that the low power demand of the weekend days is averaged out by the working days, creating a middle profile between the average working day and average weekend profiles.

Finally, there is no difference between the average weekend profiles, as shown by the red lines. The adjusted dataset only removed the school holidays that fell on working days (Monday to Friday), and not the weekends. For this reason the averages for both datasets resulted in the same power demand profiles.

One observation is that the separation distance (or the difference between the values) between two datasets for both the average working day profiles (blue lines) and average day profiles appear to be different. The possible reason for this could relate to how the program calculates the average profiles. The holidays account for seventy working week days (or fourteen working weeks). If this number of days is related to both the number of days in the full data set (365 days) and the number of weekdays in the dataset (261), holidays represent 19% and 26% respectively. This different proportion of number of holidays in the datasets impacts on the average profiles, resulting in the different gaps between the average weekday and average day profiles.

Figure 57 clearly outlines why care must be taken in the interpretation of average demand profiles, as they are heavily influenced by the data used in their generation. The figure also demonstrates that the removal of holidays creates a different profile than if holidays are included. Thus, it is important to clearly define what data has been included (or more importantly excluded) when generating average power demand curves especially if comparisons across schools are being made that may have different

holiday for instance. The decision was made that for consistency, data from periods of school holidays would be omitted from the analysis datasets. However, the next decision related to removing the appropriate holidays from the dataset.

Two possible options were available with respect to school holidays. The first was to remove the holiday data completely from the database, resulting in each school having only 295 days in a year as opposed to the customary 365 days (excluding leap years). This would allow a fairer comparison between each of the seasons, especially in summer when there is a disproportionate number of holidays at this time. An alternative solution was to edit the database to remove only working days from the holidays (i.e Mondays to Fridays) and keep the weekend profiles. The main reason for keeping the weekend holiday data was that the school could still be used by the community or by sports clubs during the holidays. The schools generally are still shut during the week, with limited if not any use by the community. It was decided that the second option would be implemented as it was felt more appropriate as a method of preserving details on weekend energy usage.

Various options exist for the removal of working days contained within holiday periods. The first option was to determine when the school holidays occur (by contacting the school) and create an automatic filter to remove these days. However, this approach itself has several potential problems associated with it. Days when the school was closed (due to bad weather or other random circumstances) would not be accounted for, hence would not be removed. Additionally, different local councils implement different school holidays which could result in non-school holidays being removed as well as school holiday days not being removed.

Another approach is to rely on a purely visual approach for to identify holidays. In this method, the power demand profile for each school is plotted on a twenty-four hour axis, producing 365 profiles. From the subsequent graph, low power demand days can be removed, on the assumption that they represent holidays and not periods when the monitoring devices are not active. However a major disadvantage of this approach is that other days such as weekends, could also be removed by error.

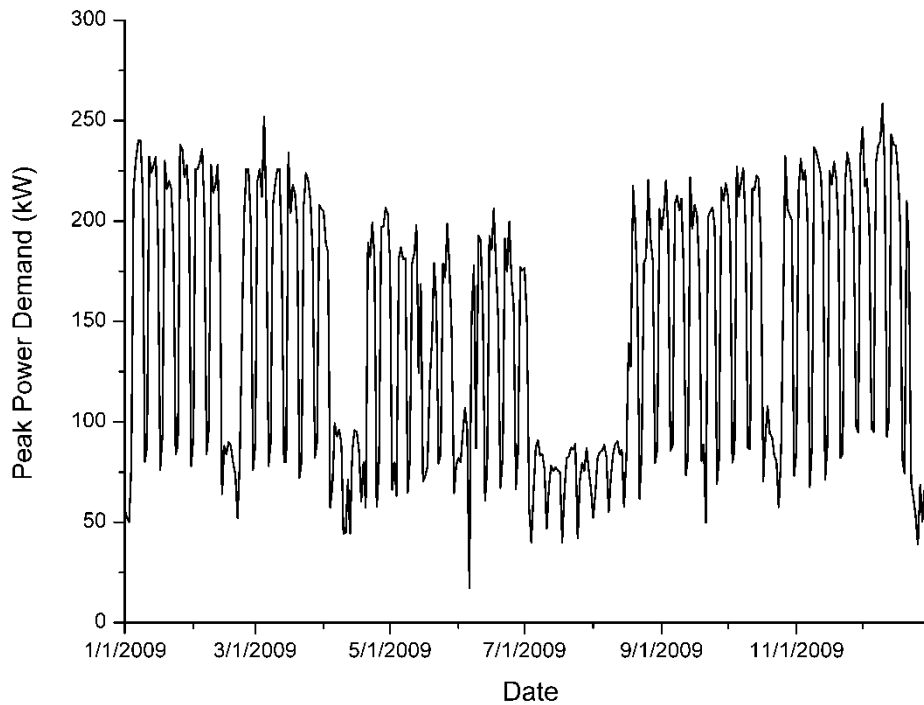


Figure 58 - Daily Peak Demand for One Year

The last method for removing holiday data was based on daily maximum peak demand and how it varied throughout the year. In theory, the peak demand in each day should slowly vary throughout the year, as energy requirements adjust for increasing/decreasing light levels or heating and/or lighting. Any sudden change ie a drop in “normal” power demand would indicate a more significant power event, such as the weekend or holidays. Figure 58 demonstrates the daily peak demand for a sample school for an entire year, and also provides an example of the maximum/minimum output as discussed in section 3.5.6.

Several outcomes are clearly visible in this graph. The variation in peak demand does slowly vary throughout the year, with winter having the higher values and conversely summer with the lowest demand. This is represented by the dips in peak demand. The second visual outcome observed in this figure is that each weekly peak demands result in an arch shape (or rise, peak and fall in power use). This indicates that there is a typical weekly power demand, with periods of high peak power demand (weekdays) and those with low peak demand (weekends). The last important outcome observed in the figure is that there are periods of low peak power demand that occur throughout the year. Examples of these low periods can be highlighted between July and September and April and May. These low peak demand times were assumed to be holidays.

A combination of all three methods was used to clean the data in relation to the removal of school holidays from the dataset. As a safeguard school holiday dates were determined by contacting the corresponding councils who provided data for the database confirming the appropriate holiday data has been removed from the dataset.

An additional approach would involve the analysis of the data in separated blocks, based on term times as an alternative to a monthly or annual based analysis. The advantage of this approach is that holidays would not form part of the supplied data and hence would not have to be removed. However, even restricting the supplied data to term times does not eliminate some requirement to clean the data due to unscheduled holidays.

3.6.2 *Half Days*

Another important factor to consider in relation to power demand in schools is the impact that half days could have on the subsequent profiles. Unlike other non-domestic buildings, schools may not work a standard “9-5” workday, five days a week. Several local authorities introduced half days each Friday, with the school closing at around lunch time (from 12:00 to 13:00 depending on the specific local authority). Initially, the inclusion of half days was not considered as this information was unknown. Only when plotting the power demand profiles for each school did it become obvious that there were instances of lower power demand. Following the removal of school holidays and weekend power profiles, there were still some unexpected demand profiles in some schools that did not appear to be random in nature. These unexpected demand profiles were identified as being associated with half day power demand in the affected schools.

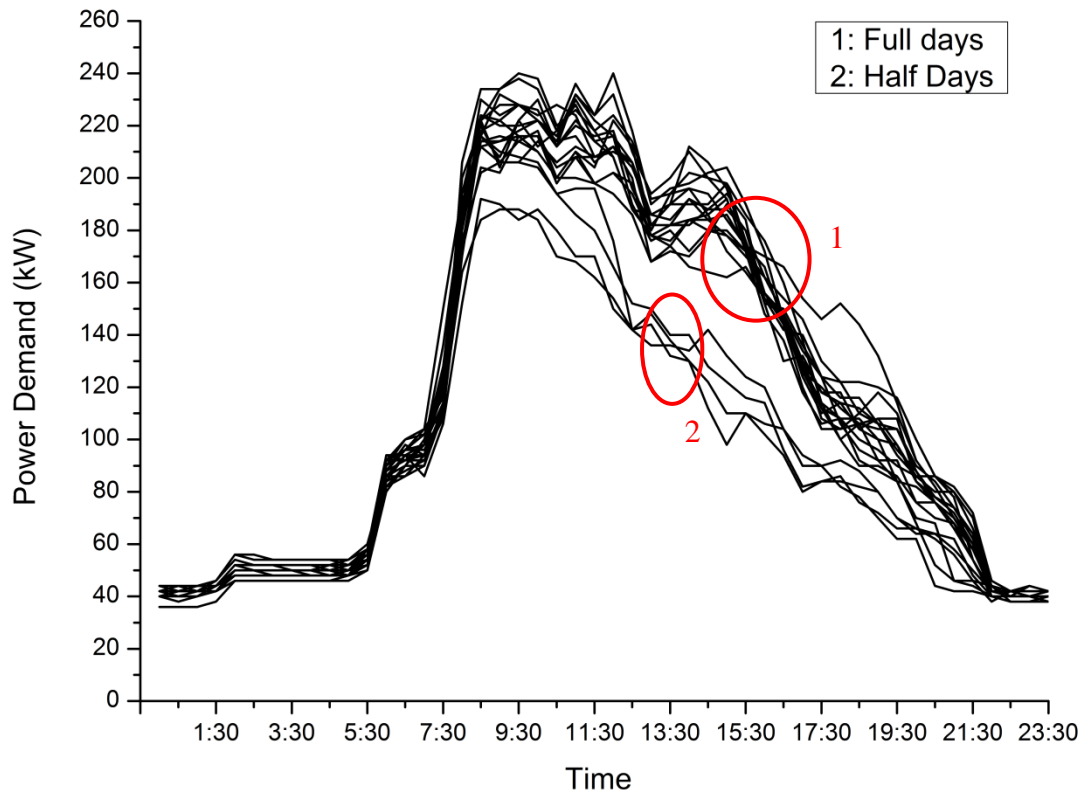


Figure 59 - Examples of Half Day profiles

Figure 59 demonstrates an example school with half day power demand profile, as well as full day power demand. The profiles shown in the figure only represent a small number of days, and as such do not represent full year. The figure highlights the key differences in power demand profile between the full day and half day power requirements. Although the two different power demands appear to have a similar profile up to around 09:00, when the power demand profiles appear to plateau the subsequent peak power demands are different. The peak demand for the half days (2) was around 180kW, in contrast to the full day demand (1) value of between 190-240kW. This is an unexpected finding as it was originally assumed that the power demand would follow the full day profiles until 12:00-13:00, where it would begin to fall at a higher rate. The difference could be due to certain departments not being fully utilised, as a result of the short teaching day. An example could be reduced catering or demand on sports halls (that have large lighting loads).

Figure 59 is very useful in highlighting the power demand difference in half days. Due to this obvious power difference, it was necessary to remove half days from the dataset used to generate typical power demand profiles.

It should be noted, that not all schools have half days (with only 58% of the schools in collected database having half days).

3.6.3 Time Correction

Another factor that was considered as part of the data cleaning exercise was the impact that changing clocks from British Summer Time to daylight saving time in winter months had on subsequent generation of typical power demand curves.

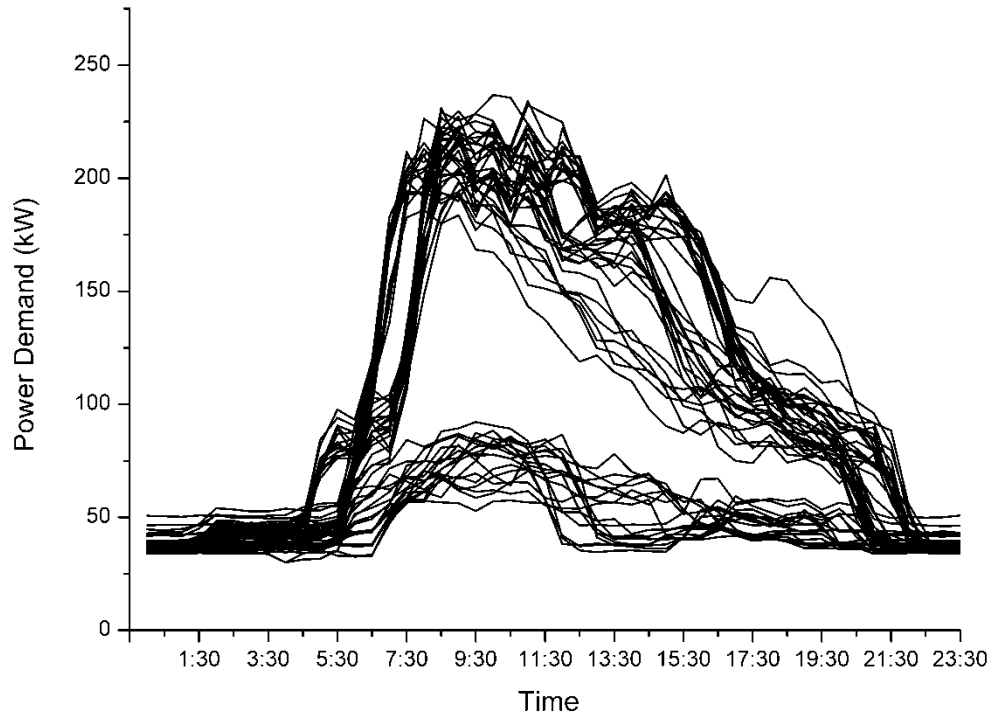


Figure 60 - Profiles Demonstrating the Changing Clocks

Visual analysis of the impact of changing from British Summer Time to Daylight Savings Time is shown in Figure 60, and represents one of the studies schools. Only when the seasonal profiles were investigated did this impact become apparent.

The figure indicates that there are two sets of profiles both having a very similar profile. The key difference is that the profiles are out of synchronisation by one hour. This is more apparent by investigating the main rise and falls in power demand. The first rise in power demand from baseload occurs at 04:30 and returns to baseload at 21:00. In comparison the second profiles power demand starts rising at 05:30 and then returns to baseload at 22:00.

In order to retain these days, the data was offset by an hour to resynchronise the profiles.

3.7 Thermal Data Cleaning

The thermal data cleaning used a similar process to the electricity data, although several additional stages were included for the monitored data. The reason for the additional stages reflected the nature of the data. The electricity data was already

presented in total energy use, whereas the monitored thermal data had to be calculated by taking the temperature and flow rates into account. This resulted in several initial filtering and cleaning stages before the primary cleaning steps (as described section 3.6) could be used. These initial cleaning stages were not considered relevant to the metered data provided by the local authorities and were therefore only applied to the collected data.

The main cleaning stages for the collected data involved filtering the temperature and flow data. For the flow data and temperature data a limit filter was applied to remove recording issues. On initial testing, it was discovered that the flow results contained several negative and unusually large values. Negative flow values were considered to be associated with the heating system being switched on and possible water turbulence causing reading errors with the monitoring devices. The data was also given maximum and minimum values. The studied building had fixed speed water pumps, producing a maximum flow rate of 26L/s and a minimum flow rate of 0L/s. Therefore, the flow data was adjusted to this upper limit. An example of the flow data cleaning process is shown in Figure 61.

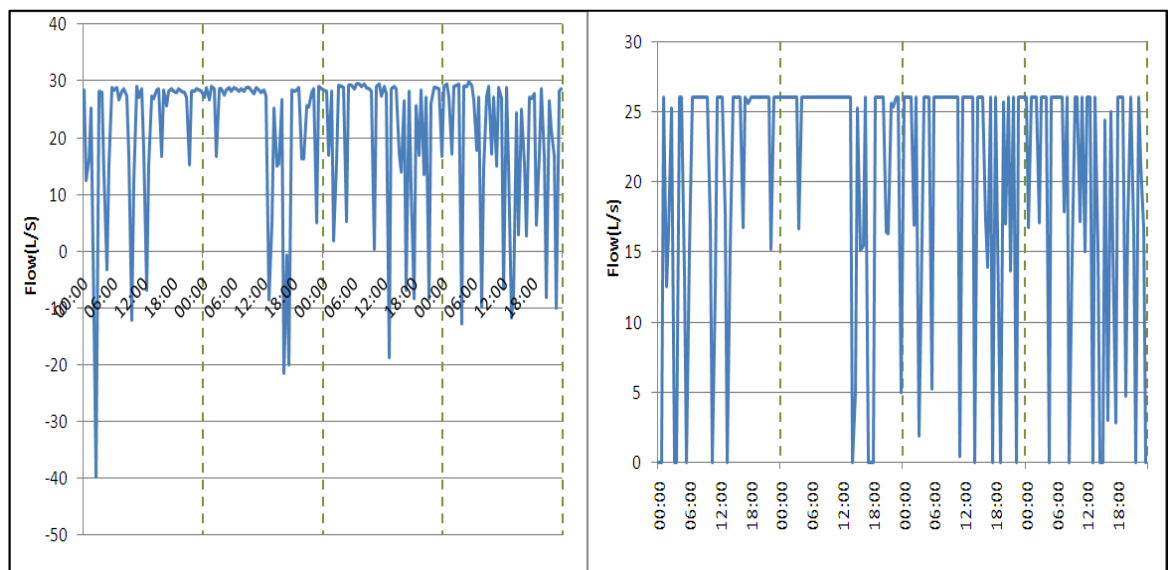


Figure 61 - Thermal Flow data cleaning process

Lastly, the temperature data was adjusted to remove any negative temperature values before the thermal consumption was calculated. The data was then subjected to the same cleaning methodology as discussed in section 4.3.1.

3.8 Accuracy and Confidence of Collected data

The ethos of this thesis was collecting energy data to determine trends in power demand. As a result, the foundation of the project is gathering suitable energy data that

is both accurate and data that has a high confidence level. In order to determine if the collected data meets these criteria, the sources of each database have to be investigated, and hence any issues or inaccuracies identified. After these issues, if any, have been identified, the level of accuracy and data confidence can be determined. The collected databases can be separated into electricity data and thermal data.

3.8.1 Electricity Data

The power demand data was to be initially recorded using energy monitors, however due to cost per unit and a limited data collection time, it was decided that the constructed electricity database would be based on meter data provided by the energy suppliers. Due to the electrical data being collected by the power suppliers, it can be assumed that this data is accurate. As a result, the confidence level in this data can also be high. The collected half hourly power demand data was processed to determine the total annual energy consumption. This calculated value was then compared to the available billing data. The comparison revealed that the collected data had the same annual consumption as the billing data. This result was as expected as the metering data used by the power companies is also the data to calculate the annual/quarterly bills.

The distribution board power demand data for the sample school was collected using multiple current transformers on each electrical distribution board. This data was not collected solely for this project, instead the database was made available by NoWatt for this research project. Unfortunately, very few details were disclosed regarding the equipment used by NoWatt to monitor the distribution boards. This would arise questions on how accurate the data would be, or what the known accuracies of the current transformers were. A key disadvantage of using current transformers (as outlined in section 2.7) is there is difficulty in detecting and recording very low power demands. This could potentially introduce further inaccuracy into the data, in addition to the equipment accuracy.

Although the accuracy of the current transformers and associated data loggers was not known, the confidence in the data was still high. It can be assumed that the same level of accuracy/inaccuracy is applicable to all the current transformers on each of the distribution boards. Due to the school not being compared to another schools distribution board data, this can be considered an acceptable source of data. The distribution board data is used to prove any assumptions made for the causes of power demand (standby, rise in demand, peak demand, etc) and not create firm conclusions. Additionally, further analysis of the main feed electrical database (non-distribution

board data) does not rely on the outputs from analysing the distribution board data. Lastly, as the data was monitored by a commercial company, it can be assumed that the monitoring service provided will be as accurate as possible, or set inaccuracy/accuracy limits set. These result in a high confidence level with this data, regardless of the unknown in accuracies of the current transformers and data loggers.

3.8.2 Thermal

The confidence and accuracy of the thermal database can be divided into two sections; NILM monitored (using the flow monitor and temperature data loggers) and metered data.

Within the NILM data, there are several areas where inaccuracies could exist; flow monitor, temperature measuring and data-loggers. The first potential errors are associated within the ultrasonic flow monitor, and in turn can be sub-divided into; sensors, pipe details and data-logger.

The correct placement of the ultrasonic flow meters is essential in recording accurate flow data. An overview of correct sensor placement is found in Figure 62.

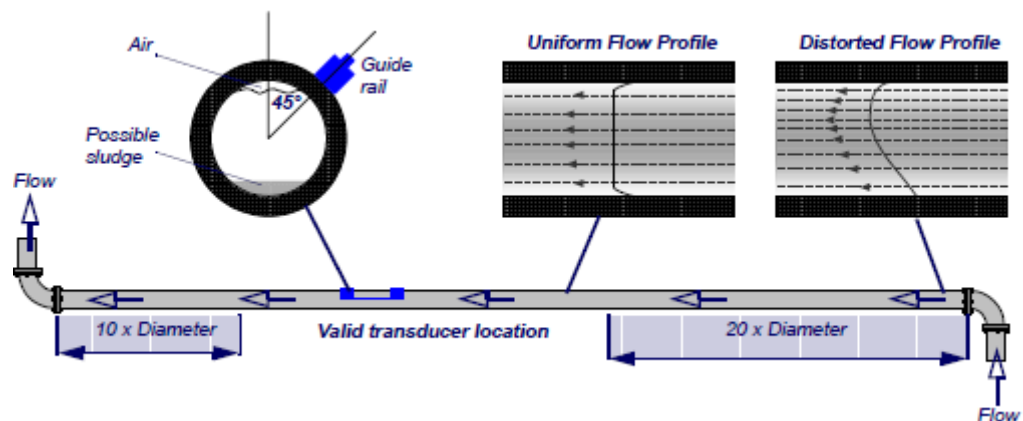


Figure 62 - Portaflow 330 Sensor Placement (Micronics, (2009))

There are several guidelines provide by Micronics, (2009) on correct sensor placement. The first is that the sensors have to be placed on a straight piece of pipe and sufficiently distanced from any bends. The guideline on this distance is 20 diameters upstream from any bend, and 10 diameters downstream from any bend (see Figure 62). This is to ensure that the water (or fluid) has a uniform flow, free from distortion or turbulence. Any existing turbulence or distortion would impact on the ultrasonic pulse, and hence provided inaccurate results. The sensors additionally have to be placed at a 45° angle in relation to top dead centre of the pipe (see Figure 62). Experimentation from Micronics, (2009) found that this was the optimum angle to provide consistent

results. This angle most likely removes the errors cost by air pockets forming at the very top of the pipe.

The final potential issue of the sensor side of the Portaflow 330 is accurately setting the separation distance between the sensors. The calculated separation distance is an accurate calculation output and presented in mm (e.g. 300.85mm). The difficulty arises when attempting to set this accurate distance using the provided sensor steel rule. However it was deemed that any error in setting the separation distance would be small and hence acceptable. Lastly, the data-logger had an in-built (or recognised) accuracy of between $\pm 0.5\%$ to $\pm 6\%$ depending on flow speed and pipe size. The accuracy for the data logger for the installed school setup was $\pm 0.5\%$ to $\pm 2\%$.

The second potential errors with the thermal demand NILM system is pipe details. Determining pipe details were an important stage when installing the thermal NILM system. It was imperative that the correct pipe dimensions are imputed into the monitoring system, as the data-logger uses these details to calculate the separation distance between the sensors. Any error in measurement of pipe thickness or diameter will result in an inaccurate calculated separation distance, hence inaccurate measurements of flow/thermal demand. Additionally, if the pipes become clogged, or lime scale (or other material) builds up within the pipe, both the relative pipe inside diameter and the water flow would be affected. This in turn would provide false readings from the monitor which would not in fact reflect the true thermal usage of the building.

The third potential errors with the thermal demand NILM system could be due to the temperature sensors and associated data-loggers. Two K-type thermocouple were attached to the common inlet and outlet pipes of the boiler system. The thermocouples were attached to one QuadRTD 4 Channel Temperature data-logger (MadgeTech, (2011)). The QuadRTD has a calibrated accuracy of $\pm 0.1\%$ as well as an time accuracy of ± 1 minute/month. To ensure that there was no continual drift of the data-logger time, the recorded data was downloaded every four weeks, and the data-logger clock resynchronised with the connected laptop (used for downloading the data). One issue found with the selected temperature monitoring system was that there was a delay from when the boilers were switched on (as detected by the flow monitor), and when a temperature change was detected. This is a result of the water not being heated instantly by the boiler, instead being heated slowly as the water is pumped around the school. This resulted in a slight delay in thermal demand profiles when compared to gas usage data (metered data).

Lastly, the two separate monitoring systems (temperature and flow) had to be synchronised together in terms of the data-logger time and date. Both monitoring systems were synchronised using a laptop, and a start time delay was activated to ensure the systems started recording at the same time.

The monitored flow and temperature data were converted in kWhs using Equation 4. The data was compared with gas meter data, as provided by the energy supplier several months after the installation of the thermal monitoring equipment. The results of the comparison between the metered gas use (in m³) and the NILM gas usage are shown in Figure 63.

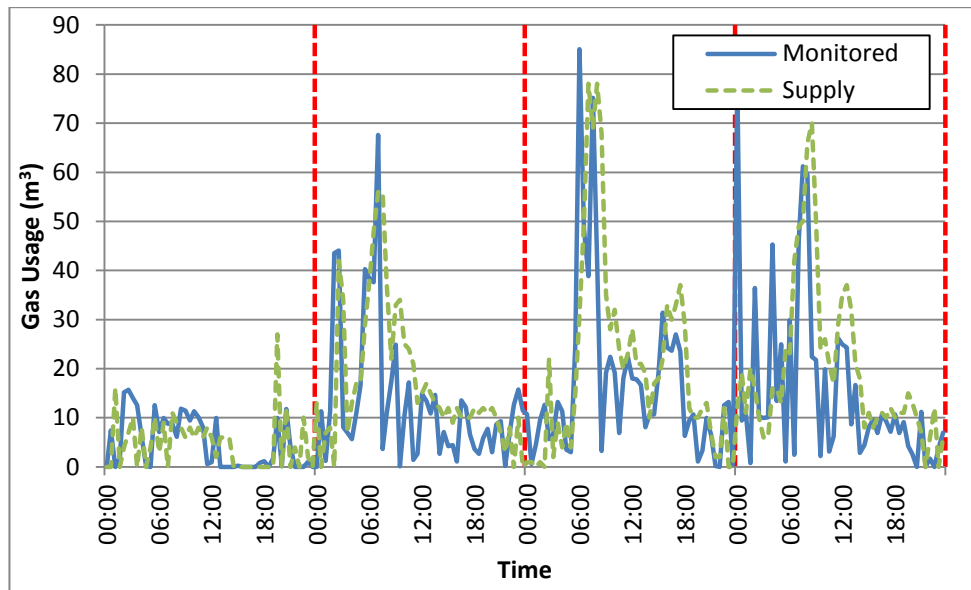


Figure 63 - NILM versus Metered Gas Demand Data

The results demonstrated that the NILM demand profile (monitored) and the metered demand profiles (supply) were similar. The NILM data was found to be 70-80% accurate in comparison to the metered data. Differences are apparent, as a result of the discussed recorded errors (as well as the data filtering, see 3.7). Additionally, the metered demand data represents total gas demand, and hence includes kitchen and science lab use. In comparison, the NILM data only represents the boiler gas usage. The comparison determined that the derived NILM methodology was accurate in determining the thermal demand of a building.

The installation of the thermal monitoring system determined that the methodology could be used to determine the thermal power demand of a building. Several months after the installation of the equipment, metered gas demand data from the energy suppliers was made available for the same school. In addition, data from several other schools was also made available. This removed the requirement of installing NILM equipment in multiple schools. A key advantage of this data is that it is

more accurate than the NILM data. Additionally, due to the data being provided by the energy supplier, it can be assumed that the data was very accurate, and that there can be a greater level of confidence in the data (opposed to the NILM data). Due to this increased confidence and accuracy of the data, the constructed thermal database consisted of meter data (from the energy suppliers) and not NILM data.

3.9 Case Study Buildings

The collected energy demand databases, as well as the available corresponding building data were compiled into separate files, based on building type, and energy type. The following sections are an overview of each database.

3.9.1 Schools

The collected data from the various sources were grouped together and a master spreadsheet file was created. This file held the key building details including the school number, type, age, number of pupils and floor area. Additionally, a check box system to establish if the school had a swimming pool, and the total annual energy consumption given in both terms of kWh and normalised by floor area.

The completed database consisted of forty-eight schools, with a wide range of construction dates, type and floor area. The completed school dataset includes thirty-two high schools, eleven primary schools and five specialised schools. Each of the type of schools are defined below.

Secondary schools, or high schools, are defined as a premise that educates children from the ages of 11 to 17 (within Scotland). A second category was defined in relation to high schools; these were defined as specialised high schools catering for non-mainstream pupils. These specialised schools represented 16% (or 5 out of 31 high schools) of the studied secondary schools, but because of their small floor area and small pupil number, it was considered appropriate to analyse these buildings separately from each other especially as specialised schools tend to be smaller in terms of pupil numbers, size of school and have smaller class sizes.

A further classification within high schools is the inclusion of swimming pools. As discussed in section 2.9, swimming pools do consume electricity, although usually not as a result of heating the water but more as a result of pumping warm water to the swimming pool, the associated pool room Air Handling Units (AHU's) and to clean the filters (back washing) as outlined in Carbontrust, (2006d). Swimming pool rooms are constantly heated to both provide a comfortable surrounding temperature, and to

minimise condensation (which in turn can lead to possible corrosion of swimming pool structure). It is important to consider this added electrical consumption as part of the power demand profile of the school with a swimming pool.

In contrast to high (secondary) schools, primary schools are defined as the first stages of education, catering for children aged from 5-11. Primary schools tend to be considerably smaller than secondary schools, as well as having smaller pupil numbers. An overview of the studied schools is presented in Table 5. The three categories of school are defined as High School (HS), Primary School (PS) and Specialised School (SS).

Table 5 - School Overview

School	Type	Year of Constriction	Pupils	Floor Area (m ²)	Pool?	Total Annual Elect(kWh)	Total Annual Energy/Floor (kW/m ²)
School 1	HS	1983	782	8042	✓	667233	82.97
School 2	PS	1978	389	4082		225060	55.13
School 3	HS	2009	933	16852	✓	965668	57.30
School 4	PS	1960	174	2535		195221	77.01
School 5	HS	1980	275	9832		342507	34.84
School 6	HS	1989	1102	11430	✓	512819	44.87
School 7	SS	2008	59	1120		239627	213.95
School 8	PS	1968	395	4001		134220	33.55
School 9	PS	1975	367	4111		218567	53.17
School 10	SS	1966	101	2316		147378	63.63
School 11	HS	1991	923	12349	✓	863421	69.92
School 12	HS	1954	712	13145		441056	33.55
School 13	PS	1985(1930)	240	6162		388991	63.13
School 14	PS	1961	290	2515		486559	193.46
School 15	HS	1960	1423	15368	✓	695154	45.23
School 16	HS	1970	806	11535		643994	55.83
School 17	SS	1964	55	1405		299024	212.83
School 18	HS	2002	744	9168		597891	65.21
School 19	HS	1893/195/95/08	913	11742	✓	565302	48.14
School 20	HS	1978	401	11436	✓	1433075	125.31
School 21	SS	N/A	78	2304		70736	30.70
School 22	HS	1965	902	11918	✓	584281	49.03
School 23	HS	2007	936	12366	✓	903706	73.08
School 24	HS	2008	779	10284		712315	69.26
School 25	HS	2007	958	12435	✓	1104376	88.81
School 26	HS	2008	961	8835		672038	76.07
School 27	HS	1960	N/A	9561		888443.5	92.92
School 28	HS	1930/1960	N/A	14909		687511.5	46.11
School 29	HS	1940/1960/2005	N/A	13559		607708	44.82
School 30	HS	1940/1960/2005	N/A	11052		730518.6	66.10
School 31	HS	1950/1960/2005	N/A	14265		602720.2	42.25
School 32	HS	1960	N/A	11852		602720.2	50.85
School 33	HS	2008	800	10891		533486.6	48.98
School 34	PS	2006	336	8835		921173	104.26
School 35	HS	1979	776	10156		492587	48.50
School 36	SS	2006	35	3688	✓	169514.9	45.96
School 37	PS	2007(r)	260	2700		161715.7	59.89
School 38	PS	1954	396	2700		150187	55.62
School 39	PS	1937	399	2800		175733.8	62.76
School 40	PS	1910/1971	347	2967		422661.8	142.45
School 41	PS	2004	230	3515		497888	141.65
School 42	HS	1975	892	11927	✓	945627	79.28
School 43	HS	N/A	6	1225	✓	235546.5	192.28
School 44	HS	1980	480	7871	✓	354727.5	45.07
School 45	HS	2009	N/A	10468		680297.6	64.99
School 46	HS	2009	N/A	11992		733254.5	61.15
School 47	HS	2009	N/A	10507		691319.0	65.80
School 48	HS	2009	N/A	13067		892522.6	68.30

3.9.2 Office

The research project originally was aimed at investigating the energy consumption of office buildings as opposed to school buildings. Unfortunately, only school data was available and readily accessible. However, data was provided by Edinburgh Council for two offices but with this low sample size analysis was limited to examining the impact of weather on the respective power demand profiles of the two buildings.

An overview of the studied offices is shown in Table 6.

Table 6 - Office Overview

<i>Office</i>	<i>Construction Age</i>	<i>Floor Area (m²)</i>	<i>Total Energy Consumption (kWh)</i>	<i>Normalised Energy Consumption (kWh/m²)</i>
Office 1	1960	12,220	2,522,480	206.42
Office 2	2007	20,717	3,232,635	156.00

3.9.3 Thermal Data

The thermal database consisted of five schools. Only one of the schools was classed as a primary school, with the other four being high schools.

Table 7 provides an overview of key details of the studied schools, and highlights the different construction ages and total gas consumption.

Table 7 - Thermal Database Overview

<i>School</i>	<i>Age</i>	<i>Floor Area (m²)</i>	<i>Total Gas Demand (kWh)</i>	<i>Swimming Pool?</i>
TS1	2007	12435	1714207 ⁽¹⁾	✓
TS2	2010	16420	1390285 ⁽²⁾	✓
TS3	2008	13035	1523229 ⁽²⁾	✓
TS4	1913	3444	418862 ⁽³⁾	
TS5	2008	10891	786837 ⁽⁴⁾	

1. 1st October (2010) – 31st May (2011)

2. 1st September (2010) – 20th February (2011)

3. 1st August (2010) – 20th February (2011)

4. 24th September (2010) – 27th February (2011)

3.10 Conclusion

This chapter described how the energy consumption data was collected and processed in order to produce the databases, which could then be analysed in order to draw conclusions. The chapter detailed how the collected raw energy data was filtered to remove unwanted profiles including blank data, school holidays and abnormal profiles. This was to ensure that the analysed data represented each building's typical demand. The thermal data was additionally subjected to conversion from gas usage (m^3) to kWhs, to allow comparison to known energy performance benchmarks.

Lastly the chapter presented the three constructed energy databases; school electricity, school thermal and office electricity. Each table presented basic building details, such as age, total floor area and building type (school electricity and school thermal databases only), as well as total and normalised annual energy consumption. The database tables (Table 5, Table 6 and Table 7) are used as a quick reference for future analysis (to determine differences between schools or offices).

The filtering and organisation of the raw energy data into separate databases allowed the analysis program to process the data to produce several useful output files. The results from this research are discussed in the following chapters.

Chapter 4 RESULTS: INITIAL ANALYSIS

The previous chapter discussed how each of the different energy databases were created, and the key outputs generated from the analysis program. This chapter focuses on the outputs from the analysis program with separate analysis of electricity and gas use. Within the electricity section, two further divisions will be discussed; electricity use within a school environment and use within an office environment. The electricity sub-divisions will be analysed separately to determine energy performance benchmarks, average power demand profiles and key trends in energy use in each building environment. Similarly, the section dealing with average gas usage profiles and whether or not the analysis program is applicable to process gas demand data for buildings.

4.1 Electricity

The electricity consumption of a building is important to analyse as it represents a sizable proportion of a building's total energy use. However this will form all of the energy use if the building incorporates electric space heating or electric storage heating. Furthermore, unlike thermal data where the majority of energy usage is associated with the heating system, electricity power demand is associated with a wide range of equipment and systems. Energy saving measures, in terms of electricity, is therefore likely to have major financial and environmental benefits. By analysing energy performance benchmarks and moving toward finer temporal resolution power data, identification of key trends in energy use as well as the associated equipment will allow targeted measures to be implemented to reduce energy wastage.

This section deals with the electricity consumption for both schools and offices. The school electricity database is considerably larger than the office database and this made it possible to do sub-analysis within the school database. The office database also included corresponding weather data making it possible to determine if a relationship existed between energy consumption and the surrounding microclimate.

4.1.1 School Initial Results - Energy Use Per Floor

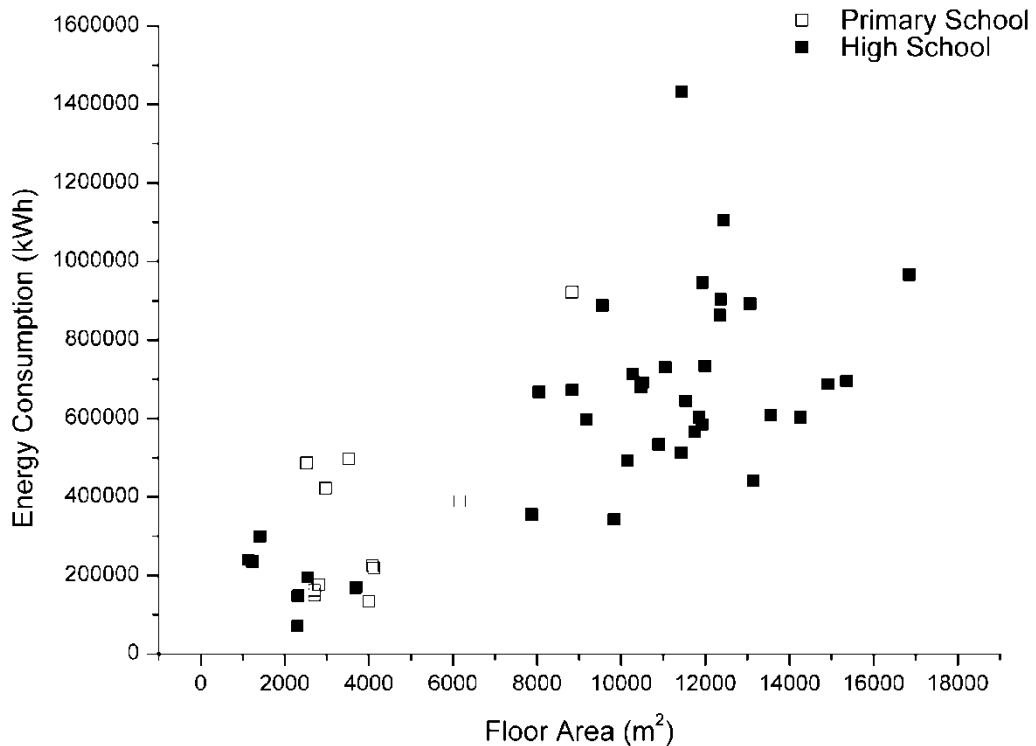


Figure 64 - Annual Energy Consumption against Floor area

Figure 64 demonstrates the annual energy consumption of the forty-eight school buildings against the corresponding floor area. The results indicated that as the floor area increased, the total energy consumption also increased. This appeared to be a linear relationship, with a residual (R^2) value equal to 0.55. The general trend indicated that as floor size increases, the total electrical energy consumption increases, as is expected.

Figure 64 also highlights the relationship between energy consumption and floor area primary schools (white squares) and high schools (black squares). The assumption was made that primary schools would consume less energy than high schools. This assumption was partially confirmed when the first cluster of data points from schools with a floor area between 0-6000m² of the results indicating that the majority of primary schools were in the lower quadrant. However certain secondary schools were identified with relatively small floor area, indicating a spectrum in the size of secondary schools. These initial results further highlight the importance of normalisation and categorisation of data as part of the analysis process.

4.1.2 School Initial Results Energy Intensity Versus Floor Area

The energy intensity (kWh/m²) for each school (as calculated in Section 4.1.1) against total floor area is shown in Figure 65.

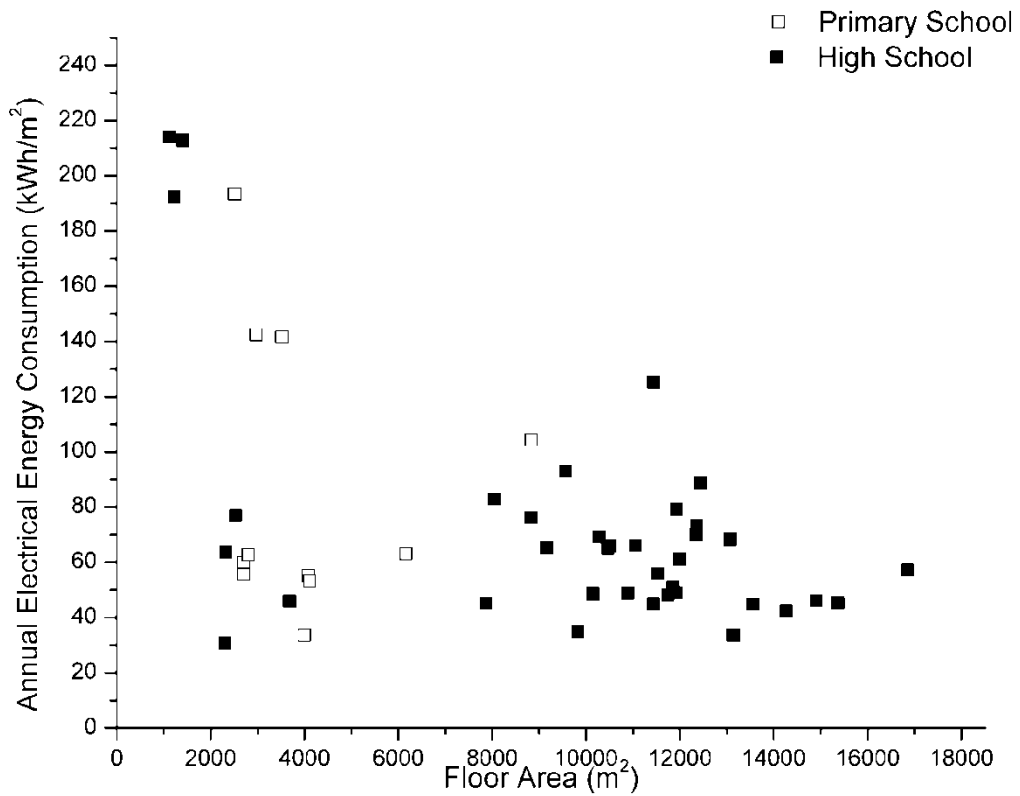


Figure 65 - Energy Intensity of Each School versus floor area

The results indicate that as the total floor area increases, the energy intensity (in kWh/m²) generally decreases. Linear regression analysis reveals that the relationship between the energy intensity and floor area has a residual value (R²) of 0.21, suggesting a weak link between the two variables. Additionally, the figure demonstrates several outlying values between less than 4000m², with values ranging from 190-213kWh/m².

4.1.3 School Initial Results – Energy per Year

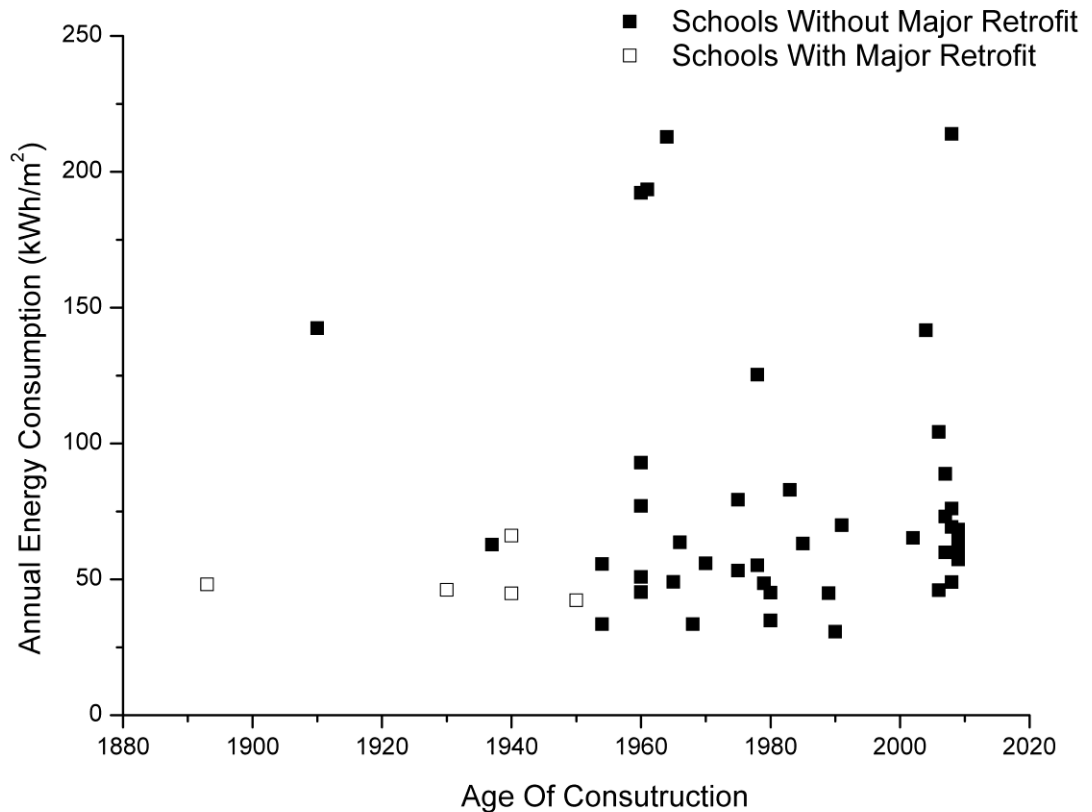


Figure 66 - Annual Energy Consumption against year of construction

Figure 66 shows the total energy consumption per square meter of each school against the construction year. Creating this output proved quite difficult due to defining the actual construction date of each school. Several of the schools are built after 2000 and their construction dates were easily established. Difficulty arose when determining the age of the older schools built prior to 2000. Several of the schools in the database were built before 1950 (and one school was built before 1900). It is unlikely that these schools have not undergone some form of retrofit since being built. The white points in the figure represented the schools that have undergone major refurbishment, including new modern extensions and equipment. It was also assumed that the schools identified with the remaining points (the black points) have undergone minor refurbishment, including upgrading windows, lighting and insulation.

The data suggests that there was not a clear linear relationship between annual energy consumption and the school construction age. It was originally assumed that newer schools (or those built after 2000) would be more energy efficient than older schools. There is a cluster of schools built after 2000 with an energy consumption range from 48.8kWh/m² to 75kWh/m². This cluster suggested that the schools have a similar energy consumption habit, or that there is a common school design/construction

the schools. In contrast, several outliers were identified. Five schools, ranging from one built in 1910, to one built in 2008, had unusually high annual energy consumption. The reason for the high energy usage in these schools is unknown at present, but it most likely reflects either the installation of electrical space heating, poor energy management within the school, or a combination of both.

Figure 66 highlights not just the trends in energy use and construction date, but also the spread of building age of the schools in the database. This database had a wide range of schools of schools between the 1950's and the 1990's, and a small cluster of newer buildings in the mid 2000's. The range of construction dates made it possible to compare how energy consumption in buildings constructed in different decades. Any differences identified are most likely due to several factors, such as different building materials, construction techniques and internal equipment.

In order to allow systematic analysis of energy consumption, the benchmark of each school type was defined. This acted as the reference point for subsequent analysis.

4.1.4 School Benchmarks

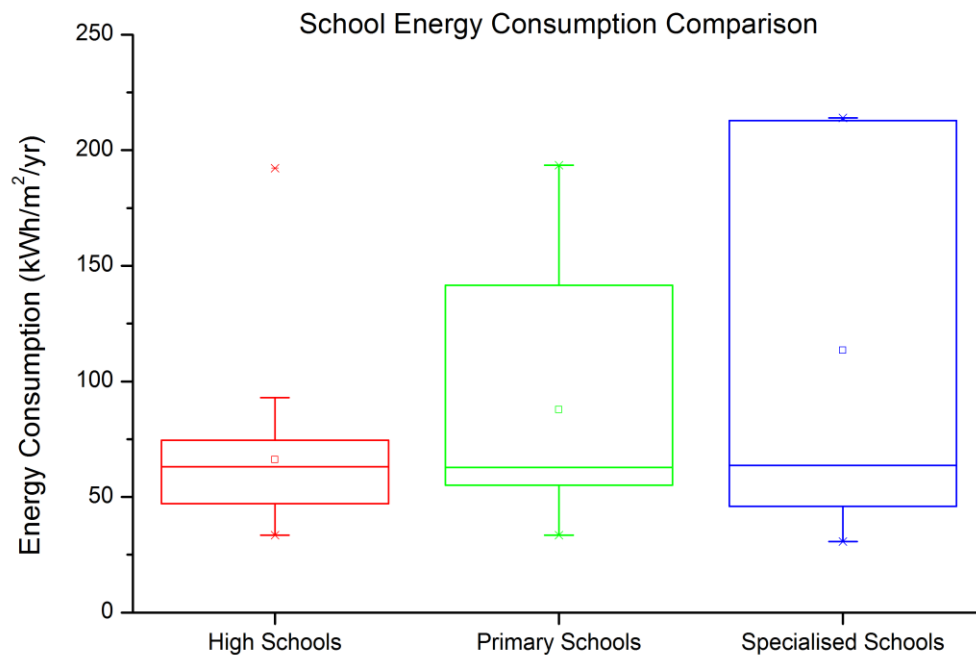


Figure 67 - Benchmarks of the Collected Energy Data

Energy consumption benchmarks were used to determine if trends or differences existed between the schools. The annual energy consumption per floor area for each category of school within the dataset is shown in Figure 67. The box plot represents the

maximum, minimum, median, average, upper and lower quartiles for a sample data of each school type.

The median across each category of school was 62-63kWh/m². This value can also be compared with the benchmarks found in (Section 2.6.2). The primary schools, based on the school benchmark table, appears to fall between the ‘typical’ and ‘bad’ benchmarks, whereas the high schools appeared to fall within the ‘bad’ category. The observation that the high schools fall into the ‘Bad’ category of benchmarks, is consistent with several of the high schools having high energy consumption

The second outcome from the benchmark analysis was that the upper and lower quartiles or the 25th and 75th percentiles vary considerably as the category of school changes. In high schools, the upper and lower quartiles are 47-73kWh/m² and for the primary schools they are 55-123kWh/m². The specialised schools have upper and lower quartiles of 46-206kWh/m².

The reason for the variation within each benchmark may be related to the sample size of the respective school types within the database. There are thirty-two schools within the high schools category, eleven within the primary schools and five in the specialised high schools. Increasing the sample size of the primary and specialised high schools to match the secondary schools may result in an adjusted variation in the respective benchmarks.

The median defined for each school category was compared to published data (Section 2.6.2). Analysis identified that energy consumption by several schools was greater than the benchmarks presented in Table 2 and Table 3, see Section 2.6.2. When the upper and maximum values were compared for each category of school, it was seen that there were several schools that consume more than the ranges of the benchmarks shown in Section 2.6.2. This finding suggested that caution should be taken when using energy performance benchmarks from previous published studies, as they may not be a true representation of energy consumption.

4.1.5 5.4.2 High Schools

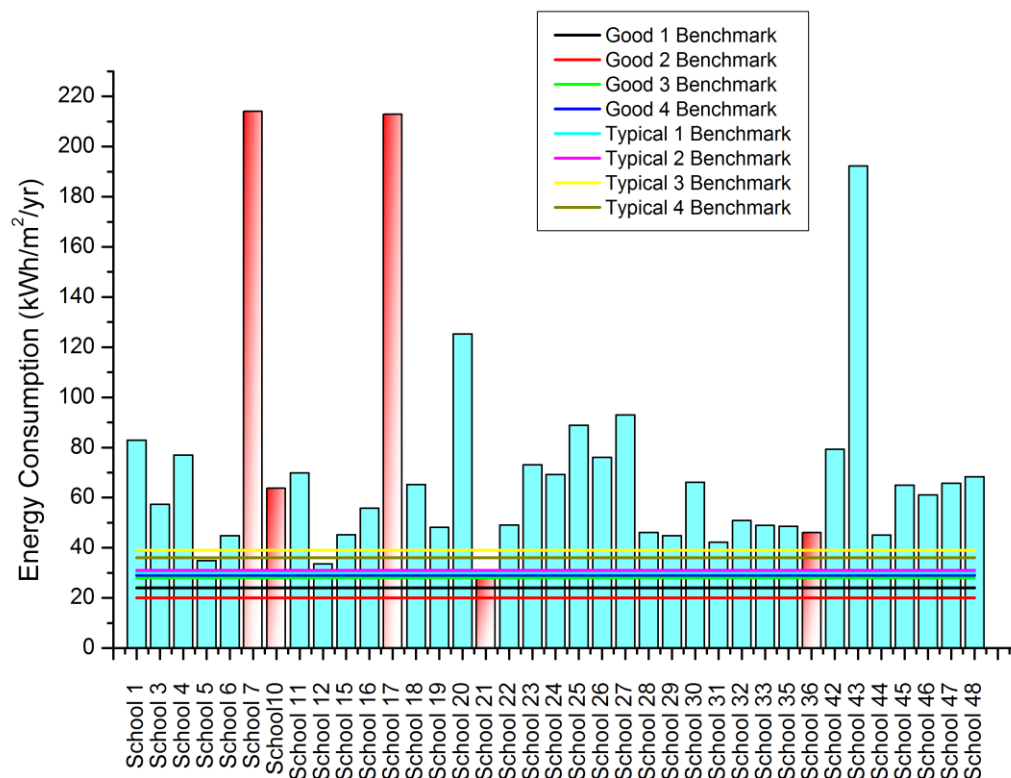


Figure 68 - High School Energy Benchmark Comparison

The annual normalised energy consumption (in kWh/m²/yr) for the high schools and specialised schools within the school database is shown in Figure 68. The energy performance benchmarks are represented by the horizontal lines in the figure. The specialised high schools are represented by the red bars, and the non-specialist high schools are represented by the blue bars within the figure.

Analysis of the high school dataset indicated that only a minority of schools fall below the high school ‘typical’ benchmarks, and none of the schools falls below any of the ‘good’ benchmarks. If the specialist high schools are excluded, a wide range of annual energy consumption was observed in the remaining schools. In this situation, only four schools (5,6,12, and 31) have an annual energy consumption within the ‘typical’ benchmarks. The figure clearly identified a school with an energy consumption of 192kWh/m²/yr which was over 900% greater than the lowest ‘Good’ benchmark, and 490% greater than the highest ‘typical’ benchmark. This finding suggested that this school had more energy intensive systems, such as electric space or storage heating than the other high schools within the database. Interestingly, two out the five specialist high schools had an annual energy consumption higher than 200kWh/m², suggesting that they too maybe operating high power demanding systems such as the various types of electric heating.

The annual energy consumption of the specialised high schools was also compared with the high school benchmarks data (Table 3, see section 2.6.2). Only one of the schools (school 21 with an annual energy consumption of 30kWh/m²/yr) falls within the any of the energy performance benchmarks.

Figure 68 reinforces the idea that several high school energy performance benchmark indicating that are available from a variety of studies, may not represent all the high schools within the UK.

When high school energy performance benchmark data is used for comparative purposes, an understanding of its limitations must be appreciated.

4.1.6 Primary School

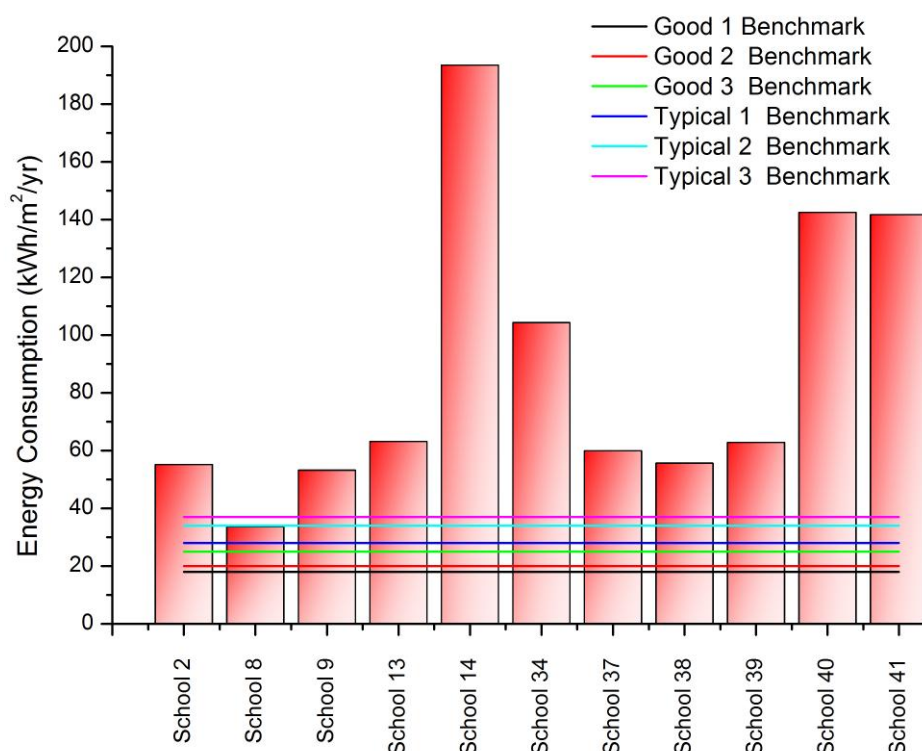


Figure 69 - Primary School Benchmarks

The next category of school used for the energy performance benchmark comparison stage was primary schools. As with the benchmark comparison carried on the total school database and high school database, the annual energy consumption of the primary schools were compared against known benchmarks (see Table 2, see section 2.6.2). The benchmarks for primary schools are generally lower than those for the high schools. The output from the analysis is shown in Figure 69, with the benchmarks represented by the horizontal coloured lines.

The results demonstrated that only one school, school 8, fell within the ‘typical’ energy performance benchmarks. The majority of schools have annual consumption at

~150% more than the highest ‘Typical’ benchmark of 37kWh/m²/yr. Schools 14, 40 and 41 have considerably higher energy consumption in relation to the benchmarks. School 14 has energy consumption over 500% larger than the highest benchmark, whilst schools 40 and 41 have consumptions ~400% higher. The high energy consumption of school 14, and to a lesser extent schools 40 and 41, could be compared to schools 7, 17 and 43 in the other categories. These schools all have high energy consumption of ~200kWh/m²/yr, and further investigation would be needed to determine why these schools have this high demand.

Overall, the energy consumption of the schools within the collected dataset is far greater than the benchmarks values. This raises a question on how representative the benchmark data is, in relation to the schools contained within the database generated in this research project. Alternatively, as the selected schools in the collected database were mainly within the central belt of Scotland, benchmarks generated from schools from different areas of the UK may not be comparable. Although the data was not available, different weather patterns in the regions of the UK could account for these differences.

Energy consumption has been used as the variable for comparison between the collected database and the energy benchmarks (see section 2.6.2). An alternative approach to determine trends and patterns of annual energy use, is to analyse more detailed consumption data, using a half hourly resolution as opposed to the single annual value.

This approach allows for detailed power demand profiles to be generated for individual buildings to allow periods of peak and low demand over a period of time. Thus it becomes possible to compare the demand profiles of different buildings and to identify variations of power usage during a given time period.

4.2 Example Profile

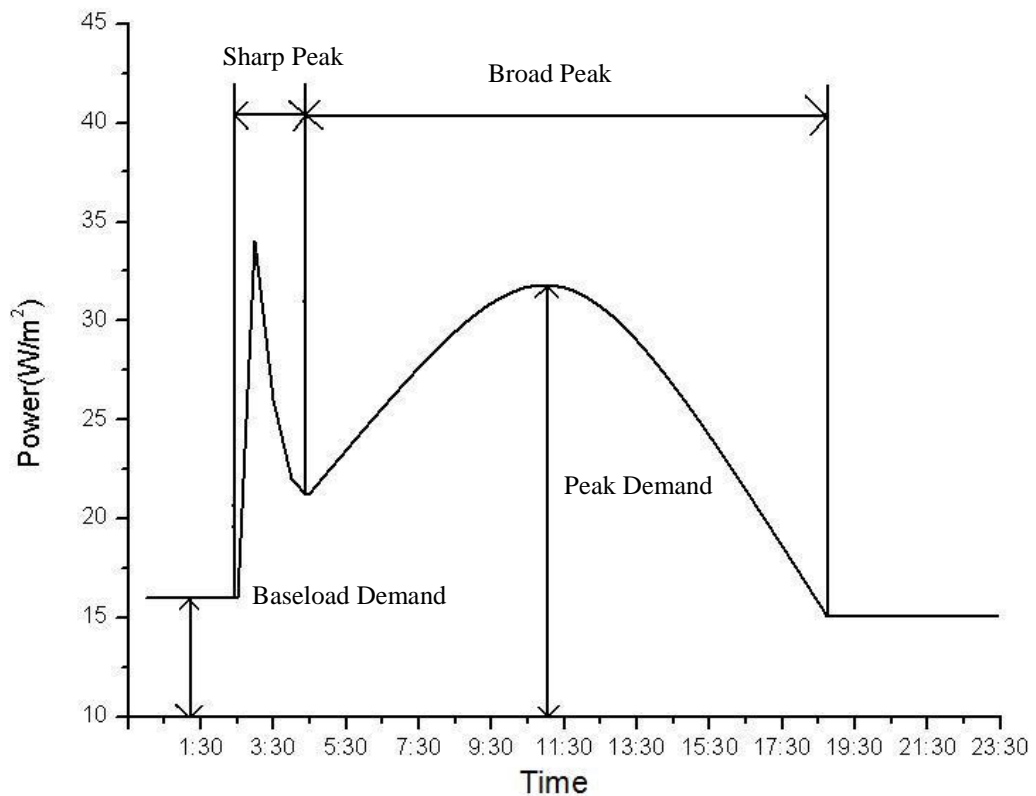


Figure 70 - Power demand profile with key terminology identified

An illustrative example of the features of a power demand profile is shown in Figure 70. In this example, the power demand is defined over a 24 hour period. The key features of the power demand profile are; a) the baseload, b) the peak demand, c) the sharp peak, and d) the broad peak. The baseload demand can usually be defined as the minimum demand that occurred in the data sample. This baseload is considered to arise from equipment being constantly used, and equipment in standby mode. The peak demand is normally defined as the maximum demand that occurred in the sample data.

However, in this example, although the sharp peak has the higher power demand, it is considered a ‘spike’ and not the true peak demand. Another important parameter in the power demand profile is the concept of the broad peak. This can vary with time, buildings and seasons. In the example shown in Figure 70, the sharp peak occurred from 02:00 to 04:00 with a peak demand of 34W/m². In contrast, the broad peak occurred from 04:30 to 18:30, and reach a maximum power demand of 33W/m². Baseload demand returned to its background level 18:30 to 23:00.

The daily power demand profile for each of the schools making up the collected dataset was collected over a one year period. The daily profiles were merged to generate the average annual power demand profiles for each of the schools.

4.2.1 Average School Profiles.

The analysis in the previous section focused on annual energy consumption of schools within the database, and compared annual energy consumption against previously established energy performance benchmarks. In this section, the average power demand profiles for each of the schools were analysed to gain an insight into how power is used within the schools. The individual school power demand profiles were compared against each other, and by investigating half hourly power demand data (instead of annual consumption data) key trends and power events were visually identified.

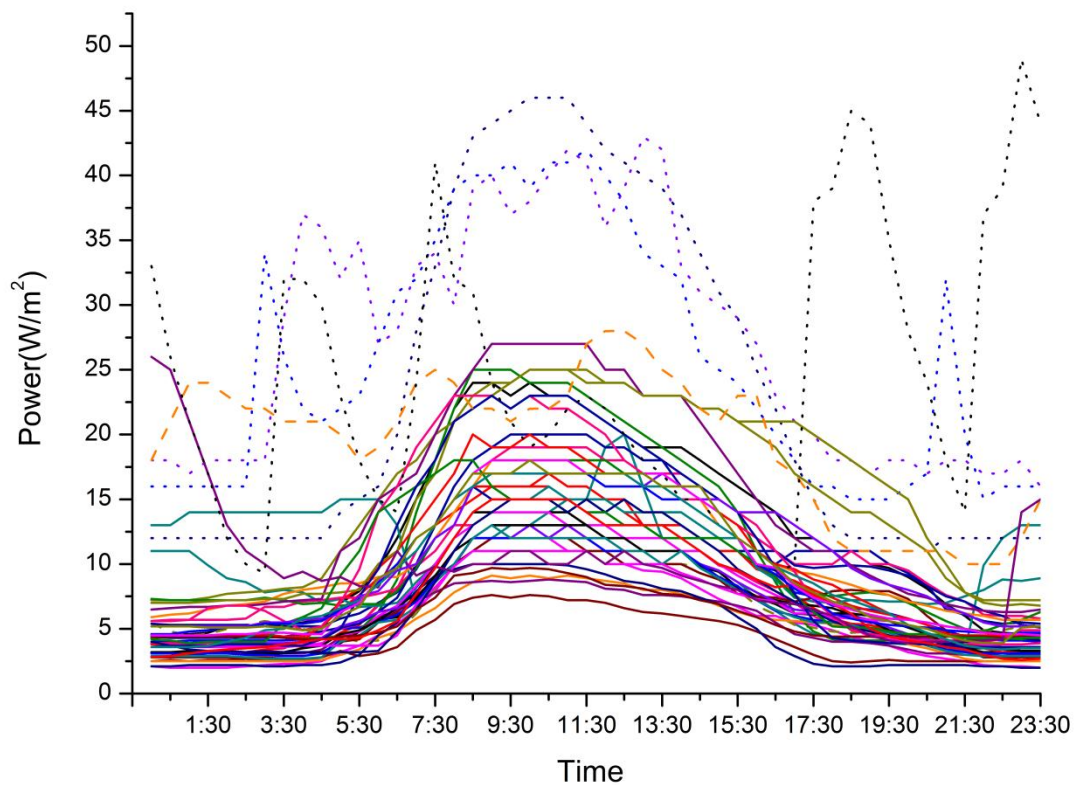


Figure 71 - Average Annual Power Demand Profiles

The average power demand profile, representing an average daily demand for each school within the school database was calculated and plotted, see Figure 71. Each profile represented the weekly average demand for a school but did not include any weekend or holiday power demand data. The figure highlights the variation in power demand profile shapes and the differences in peak power demand as well as baseload values over the 24 hour time period. The majority of the schools displayed a similar power demand profile. However, several of the schools give rise to distinct power demand profiles, which were at variance to the power demand profiles of the majority of schools.

Examples of such profiles are represented by the dashed profiles, shown in Figure 71. It is important to understand why these schools produce the ‘non-typical’ profiles. Possible reasons for the ‘atypical’ profiles could be different occupant behaviour, different building construction, school category and different heating fuel type.

To better understand the differences between the schools that have a similar demand profile, and the schools that have atypical profiles, further detailed analysis on power demand within these two groups was undertaken. It is useful to further analyse the schools in further detail to determine how power is used, and why variations in power demand between the schools exists.

4.2.2 Example School Profiles

To determine how the power demand varies across the schools, and the possible reasons for the variation, several example schools were chosen and discussed in further detail. Additionally, seasonal influence was introduced into the analysis for the three selected schools, representing each school type.

The three example schools selected for further detailed analysis were school 11 (representing high schools), school 39 (representing primary schools), and school 7 (representing the specialised high schools). Each school was analysed in turn, and key results and outputs discussed

The first stage of the analysis was to create the average annual demand profiles that represent the average working weekday demand and the average weekend demand for each school. The data was normalised by floor area.

4.2.3 Example School Analysis: School 11(High School)

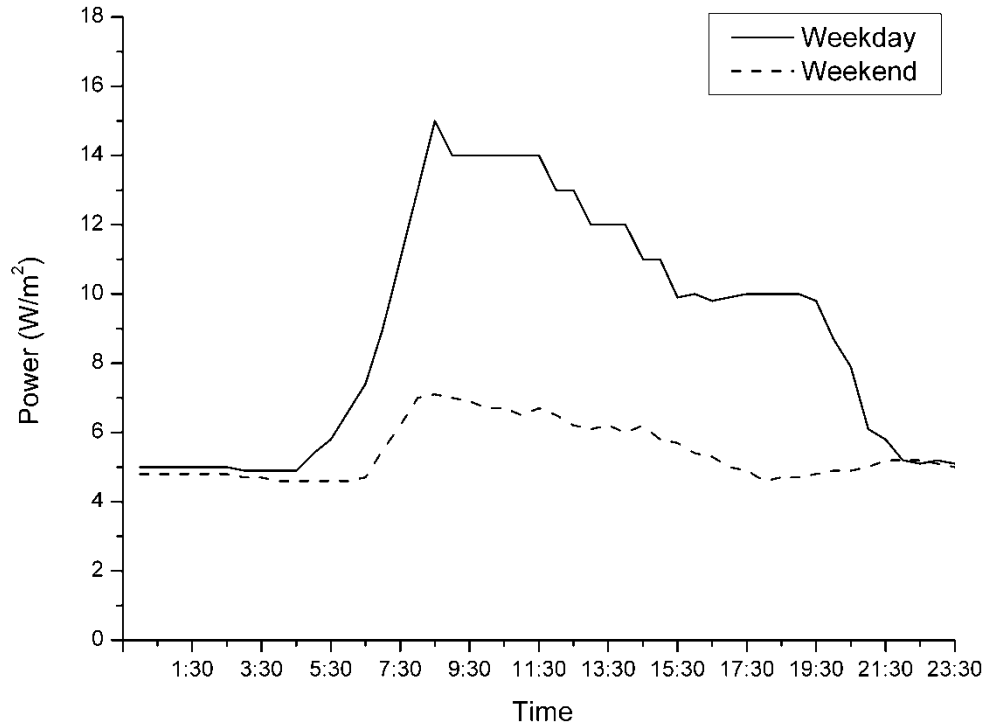


Figure 72 - School 11 Power Demand Profiles

Figure 72 represents the daily average power demand profiles both for a typical weekday (solid line), and a typical weekend day (dashed line) for school 11. The profile shape for weekend and weekday were broadly similar, but differed in magnitude of power demand (weekday greater than weekend). Peak power demand on weekdays was 15W/m² and 7W/m² at weekends, with both peak demands occurring at 08:30. Although there was a difference in the magnitude of peak demand between weekday and weekends, the power demand fell after peak demand at 08:30 to 21:30. However, even though peak demand fell over this period, a notable difference was observed in the weekday power demand profile. A plateau was observed between 15:30 and 19:30 with a power demand in the region of 10W/m². Both power demand profile returned to a similar baseload value of ~5W/m² at 21:30 and remained at this level until early morning. Interestingly, a rise in power demand occurred at 04:30 during weekdays, and 06:30 at weekends.

As expected, the power demand profiles for school 11 differs between the weekdays and weekends. This difference is primarily driven by the magnitude of power demand although a difference does exist during weekdays from 15:30 to 19:30. The initial difference in magnitude (before 08:30) is consistent with user interaction of power systems, such as switching on heating systems, general lighting, equipment and other I.T services. It should be noted that school 11 has a centrally controlled heating

system, with the Council determining when and for how long the system is used for. This initial rise in power demand could be associated with the heating pumps and AHU’s switching on as a result of this control system. Increased demand after this time, would mainly be the result of class room lighting, additional heating (increased use of AHU’s) and additional equipment such as computers, projectors and interactive white boards.

Clearly these demands will not be required during the weekend, although some heating and lighting will still be required, hence accounting for lower power demand profile. Interestingly, although the rate of fall in power demand from the peak at 08:30 falls at a different rate at weekdays and weekends, the fall appears to end at a similar time (15:30). The fall in power demand over this time was consistent with reductions in heating (both in terms of electric heating pumps, and associated AHU) and school lighting.

The key difference in power demand profiles at weekdays and weekends, apart from the magnitude of the demand, was an apparent plateau that occurred from 15:30 to 19:30 during weekdays. This additional power demand was indicative of after school use during this period. Examples of out of school use include evening classes and sports clubs.

The seasonal impact on the average power demand was assessed in school 11 (see Figure 73).

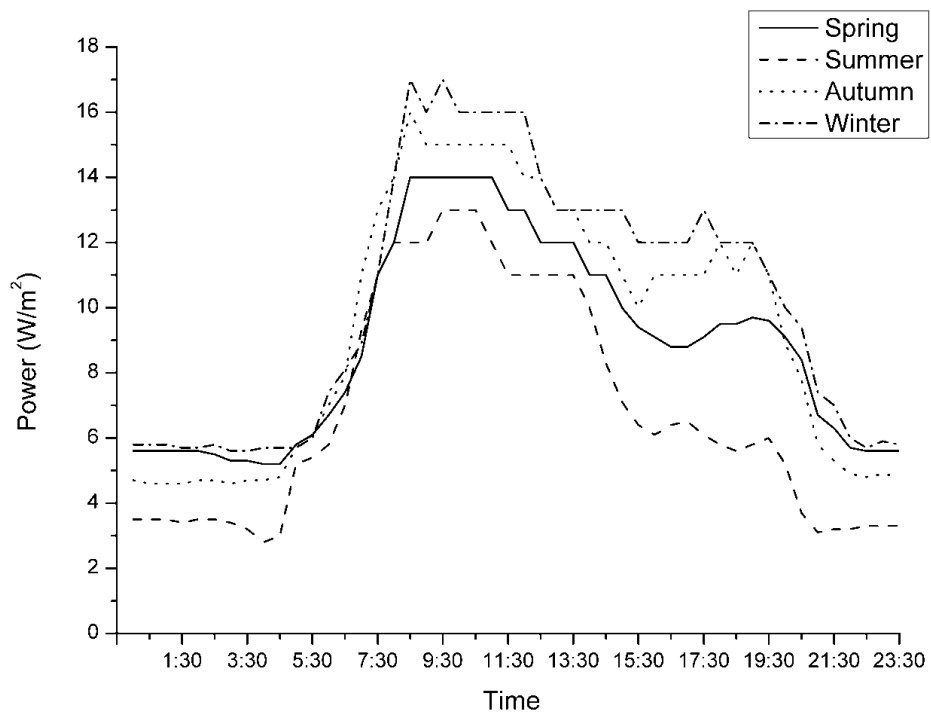


Figure 73 - School 11 Average Seasonal Power Demand Profiles

The average seasonal power demand profiles for school 11 for spring, summer, autumn and winter is shown in Figure 73. The profiles can be divided into several key sections; the baseload values, the peak power demand and the after school power demand. The baseloads vary through the different seasons, with summer having the smallest ($3.2\text{W}/\text{m}^2$), autumn having $3.8\text{W}/\text{m}^2$ and spring and winter having a baseload of under $5\text{W}/\text{m}^2$. In contrast, seasonal impact differed on the peak power demand where the order was summer ($13\text{W}/\text{m}^2$), spring ($14\text{W}/\text{m}^2$), autumn ($16\text{W}/\text{m}^2$) and winter ($17\text{W}/\text{m}^2$). Lastly, the seasonal impact appeared to differ in the power demand profiles after 15:30.

The baseload power demand is derived from a mixture of systems that are continually switched on, and systems that are in a standby mode. In the extremes of summer and winter, additional background (or external) lighting would be required to compensate for longer periods of darkness. In addition, increased demand for background heating to compensate for lower indoor/outdoor temperature would also account for the different baseload values between winter and summer. Similarly, the other seasons (spring and autumn) would have intermediate power demand.

As mentioned previously, the order of impact of seasons on peak power demand differs from baseload demand. Although winter still has the maximum impact on peak power demand, and summer the least, the order between spring and autumn changed. For baseload demand, spring had a greater power demand than autumn, whereas for peak demand, autumn had a greater impact than in spring. As peak demand is the result of key systems being used (mainly lighting, heating and small power use and IT equipment), the seasonal impact on power demand is readily explained by variations in temperature, global solar radiation, and user behaviour.

The part of the power demand profile that demonstrated greatest seasonal variation was from 15:30 to 21:00. The magnitude of the difference between summer and winter was $6.5\text{W}/\text{m}^2$, compared to $\sim 3\text{W}/\text{m}^2$ for the baseload and $\sim 4\text{W}/\text{m}^2$ for peak power demand. The power demand over this period is most likely a result of out of school activities. In winter the majority of this activity will be take place inside the school, although some outdoor activity will take place which would require external lighting (outdoor pitches). In contrast outdoor activities are more likely to take place in summer, due to warmer temperatures and longer daylight. Autumn and spring would have intermediate impact on power demand with the order dependant on the proportion of indoor and outdoor activities being undertaken in the school during these seasons.

4.2.4 School 39 – Primary School

School 39 was chosen at random from the primary school database, and used to determine how the power demand of a primary school differs from other type of schools.

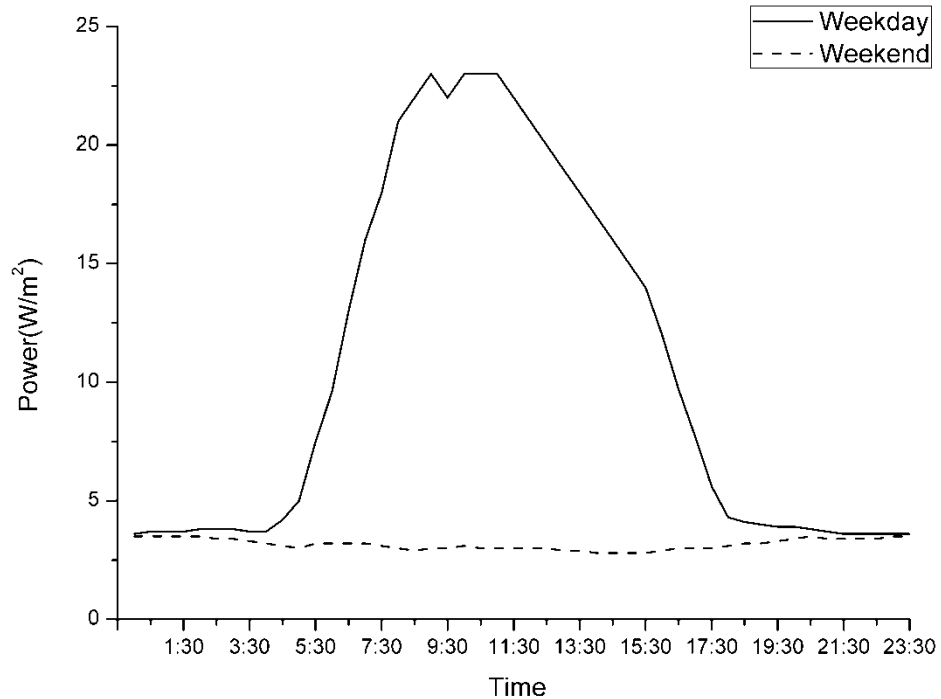


Figure 74 - School 39 Average Power demand Profiles

The average annual power demand profiles for school 39 are shown in Figure 74, and highlighted both the average daily and average weekend power demand. A pronounced difference in peak power demand was observed between weekday and weekends. The peak demand of the weekday profile showed a broad peak whereas at weekends the power demand varied little over the 24 hour period.

The baseload value was similar for weekday and weekend, with a value of $\sim 3.6 \text{ W/m}^2$. During the weekday power demand increased from 03:30 and reached a peak power demand of 23 W/m^2 at 08:30 followed by a plateau to 11:30, with demand falling to reach the baseload value at 18:30. In contrast to the increase and decrease in power demand from 03:30 to 18:30 during the weekdays, the weekend power demand varied little from the baseload value. Clearly, the power requirements and those factors that contribute to power demand differ between weekdays and weekends. Power demand during the week in this primary school is driven by similar systems that were found in the high school. The main systems include heating systems, general and classroom lighting, and IT small power. Although the primary and high school will share common equipment types, the absolute number of equipment types, such as computers, would be expected to be greater in high schools.

One considerable difference between the primary school and the high school was that there is no afterschool usage at the primary school either after school hours, or at weekends. In contrast to the profile observed in high schools (Figure 72) which showed a plateau from 15:30 to 19:30 no such plateau was observed in the weekday power demand profile of the primary school. Furthermore, unlike the high school which displayed a small rise in power demand at weekends, no such change was observed in the weekend power demand profile for the primary school. This observation can be explained by the fact that primary schools do not generally have the facilities for after school clubs in comparison to high schools.

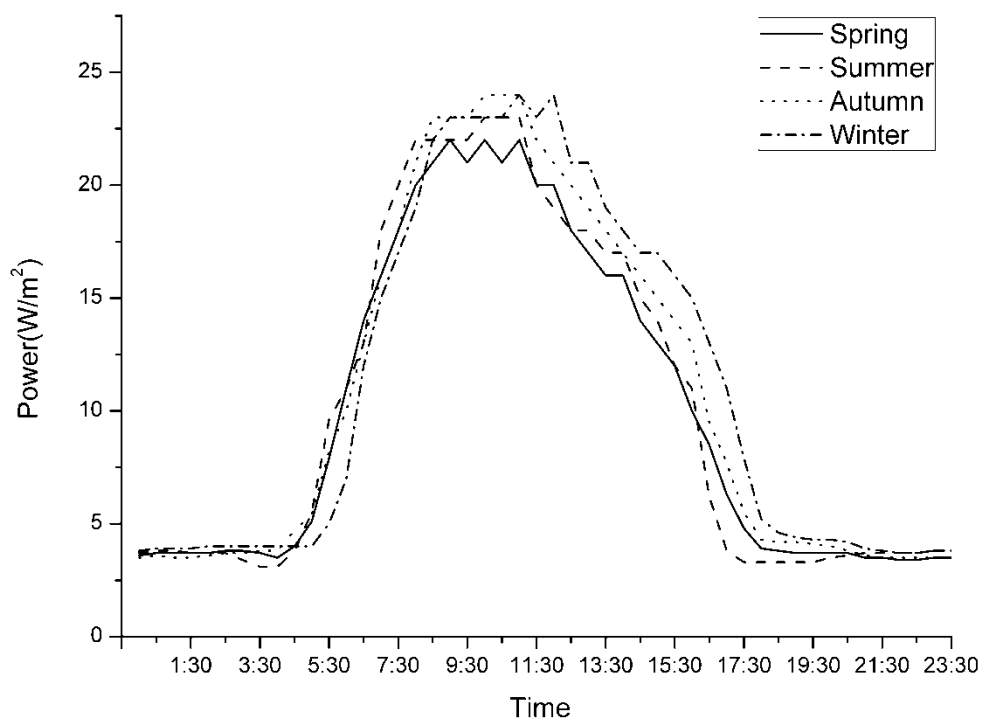


Figure 75 - School 39 Seasonal Power Demand Profiles

The seasonal impact on the power demand of school 39 is shown in Figure 75. Essentially, the seasons had very little impact on the power demand profile, with a peak demand values ranging from 22W/m² (spring) to 24W/m² (winter and autumn). Similarly, the seasons had no impact on the baseload (4W/m²) whereas a slight time difference was observed in the fall of demand from 11:30 onwards. Although differences were observed they were relatively small in nature. The fall to baseload demand in spring was reached at ~17:30 whereas in winter, this was extended to 18:30. The lack of seasonal variation indicates that there is little change in how and/or how much power is required by this school throughout the year.

This could indicate one possible scenario. The same winter demand, or increased lighting and heating, is applied across the other seasons, where potentially the level of lighting and heating is not required. The relatively high power demand of the school, poor energy management would appear to offer the most likely explanation for the lack of impact the seasons have on the power demand profile of this school.

The last example school studied in this analysis section was school 17, and represented the specialised high school category.

4.2.5 School 17 Specialised High Schools

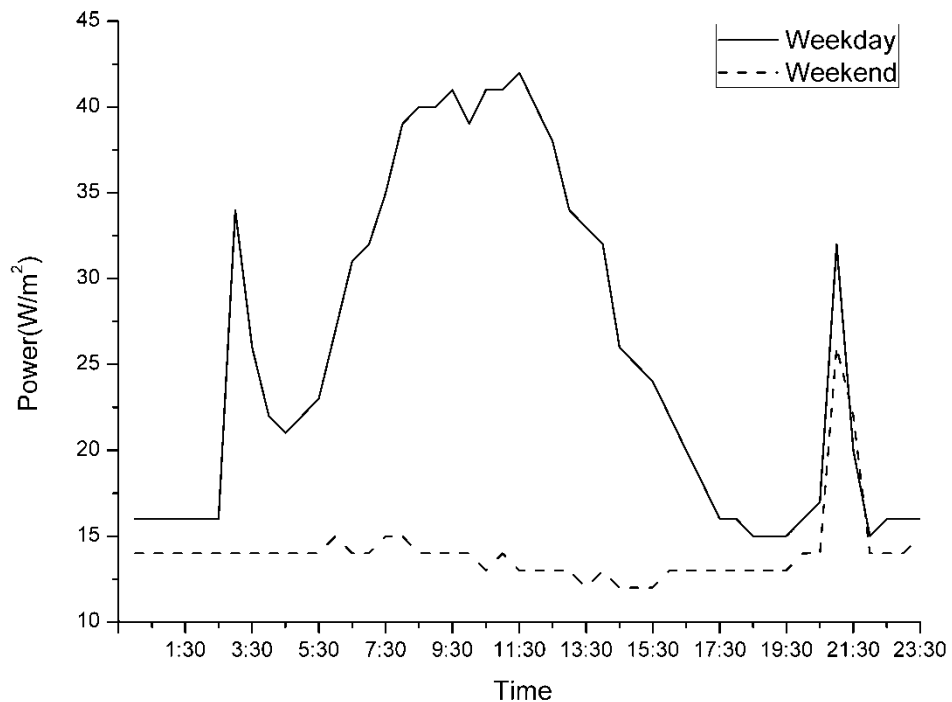


Figure 76 - School 17 Average Daily Power Demand Profiles

The weekday power demand for the specialised high school appeared to differ from both the high school and primary school. Three distinct peaks were observed, a sharp peak from 02:30 to 04:30, a broad peak from 04:30 to 19:30 and a second sharp peak from 19:30 to 22:00. The specialised high school had a similar weekend demand profile as the primary school, i.e. little variation from baseload demand up to 19:30. Where the weekend profile differed, was in the appearance of a sharp peak from 19:30 to 22:00. Interestingly, this sharp peak observed at the weekends in the specialised school matched the peak observed at weekdays differing only in a lower peak demand at the weekend.

Sharp peaks in power demand profiles are associated with intense periods of power demand over short periods of time. One possibility is that the sharp peaks are associated with electric storage heaters which are active in the early morning during

weekdays, and late evening at weekdays and weekends. The unknown systems which contributed to the two sharp peaks in the power demand profiles, appear to be switched on for a relatively short period of time; once in early morning and once in the evening.

As mentioned previously the broad peak is similar to the profile identified in the high school and primary school. The broad peak started at 04:30 and reached its peak at 11:30, with a reduction in power demand from this time to 19:30. As with the other schools, this rise and fall in power demand is related to the building’s key systems (lighting, heating, small power) being turned on and off.

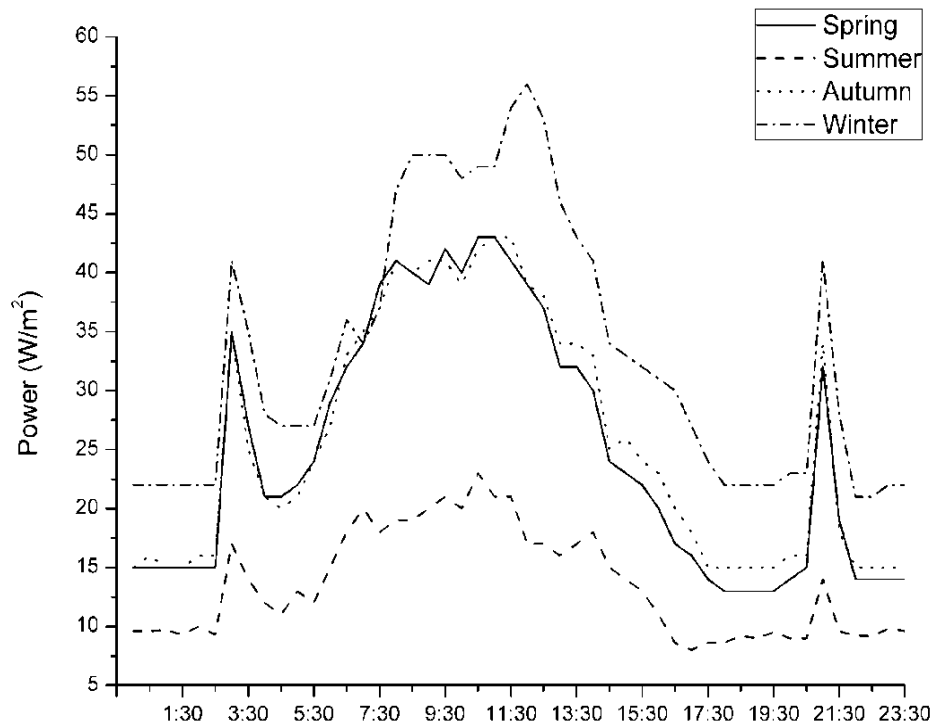


Figure 77 - School 17 Seasonal Power Demand Profiles

The effects of the seasons on the power demand for school 17 are shown in Figure 77. The seasons had a major impact on the magnitude of the power demand in this school. Interestingly, although the magnitude was affected, each power demand profile had the characteristic two sharp peaks and a broad peak. As expected, the power demand was greater in winter than in summer. This was true for the two sharp peaks and the broad peak. A further analysis of the seasonal effect on the power demand is shown in Table 8.

Table 8 - Overview of School 17 Seasonal Analysis

Season	<i>Power Demand (W/m²)</i>			
	Baseload	Peak Demand (of broad peak)	SP 1	SP 2
Spring	15	43	35(20)	33(18)
Summer	10	22	17(7)	13(3)
Autumn	15	43	35(20)	34(19)
Winter	22	55.5	41.5(19.5)	41.5(19.5)

For each of the parameters, baseload, peak demand and sharp peaks 1 and 2, the impact of the seasons were in the following rank order; winter, autumn/spring, summer. The maximum difference between winter and summer for baseload was 12W/m², peak demand was 33.5W/m², sharp peak 1 was 24.5W/m² and sharp peak 2 was 28.5W/m². Table 8 additionally demonstrates the peak demand of each sharp peak, with the baseload removed, to highlight the seasonal magnitude of each sharp peak (see bracketed numbers). These findings are at least consistent with the view that temperature and global solar radiation are impacting on the power demand of school 17.

4.2.6 Factors Contributing to Total Power Demand

Previous results (sections 4.1) have shown that the annual energy consumption and average power demand profiles differ between schools. It is therefore important to establish what factors contribute to both annual energy consumption and average power demand profiles. Several assumptions were made to describe the differences in power demand profiles between the schools, such as heating (pumps and AHU), lighting and the occupancy of classrooms. A key limitation of using total power data (from supply meter) to derive average power profiles, is that it is a summation of all the individual factors (systems) that contribute to the total demand.

One option to overcome this inherent weakness of using total power data, or supply meter data, is to attach power monitors to every piece of equipment to record actual energy usage/power demand throughout a set time period. This would create a large database of detailed power demand that covers every power consuming device and system over a given period of time. A disadvantage of this option, is that it requires an extensive amount of equipment, which is unfeasible in terms of both logistics and cost. The second option is to use power monitors on the distribution boards, as opposed to the individual equipment, and monitor the demands of each distribution board. The

advantage of this approach is that it is less costly and logistically, more feasible to undertake.

The option of using power monitors on the distribution boards was used to determine the factors (systems) that contribute to the total power demand of the selected high school.

4.3 Distribution Boards

The primary role of a distribution board is to break down the main electrical supply feed into smaller more controllable circuits. For modern buildings the distribution boards can be broken down into different departments and different electrical rings. The electrical rings could include the main lighting or power sockets, and departments could range from maths, music, to more power intensive rooms such as science laboratories and workshops. Modern distribution boards are designed and laid out before the buildings are constructed, resulting in the boards being divided into the different departments or key systems. A problem can arise due to older schools that have been retrofitted over the years with newer systems. The main concern was that the newer systems have been added to any spare distribution boards resulting in mixed output feeds (e.g. lighting mixed with power sockets). If this was confirmed, then analysing the distribution power data may not prove that reliable in determining how and where energy is being consumed in a building. A possible solution to a mixed distribution is to conduct a STEM test, as discussed in Section 2.7.5, and identifying the distribution board outputs and place a separate power monitor on the outputs.

The power demand data for key department and system distribution boards for one of the schools in the electricity database was made available. Table 9 highlights each of the recorded boards, when they generally operate and the associated systems they power. One disadvantage with the distribution board data from this source is that any results and analysis rely on the accuracy of the labelling of the distribution boards. An example of the labelling issue can be seen in Table 9. The distribution board ‘General’ was provided with very little information regarding the systems connected to this board. Thus several different systems, such as lighting, IT or plug sockets, could be supplied from this distribution board.

Table 9 - Example School Distribution Boards

<i>Distribution Board</i>	<i>Systems?</i>	<i>Distribution Board</i>	<i>Systems?</i>
1CIT	Computer Classrooms	TechCraft	Tech equipment
GA-Chang	Changing Rooms	2BART	Art Department
HE1	Home Economics	GCAdmin	Admin Office
ITHUB	IT Server	HE3	Home Economics
PoolPlant	Pool Heating and Ventilation	MPC1	AHUs
1D Library	Library systems	ExtLight	External Lighting
GamesHall	Lighting	General	General Lighting and sockets
HE2	Home Economics	IFIT	IT Classrooms
Mech2b	AHU's	MPC2	Multiple AHUs

4.3.1 Example Day 1- Weekday

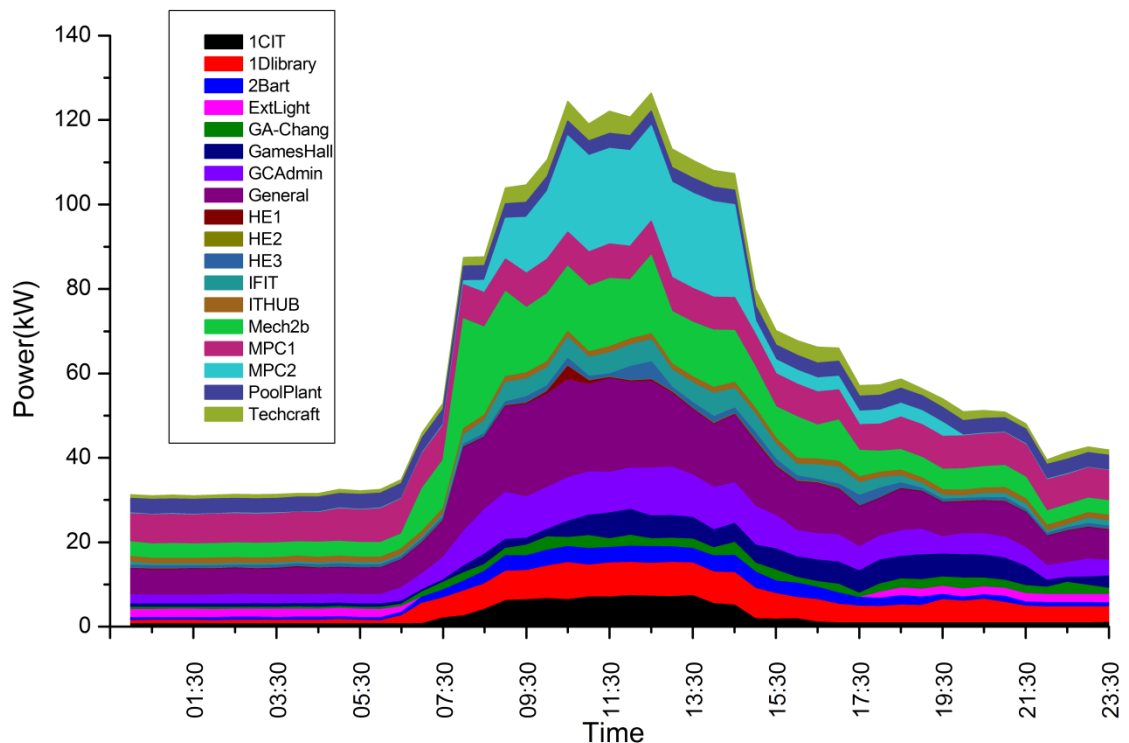


Figure 78 - Distribution Board Profiles

One sample weekday, or working day, was chosen at random from the distribution board database. The power demand profiles for all eighteen distribution

boards are shown in Figure 78. Although the individual demand profiles are broadly similar, differences existed in the peak power demand between the distribution boards. The ‘general’ and ‘MPC2’ distribution boards had the highest demand whereas distribution boards such as ‘ITHUB’ and ‘GA-CHANGE’ monitored the lowest power demand.

To understand how the different distribution boards contributed to the total demand profile, each profile was ‘sliced’ at four time points; 03:30, 07:30, 10:30 and 17:30. The time points were selected as they coincided with the key events within the power demand profile, i.e. baseload, rise in demand, peak load and fall in demand.

a) Baseload (03:30)

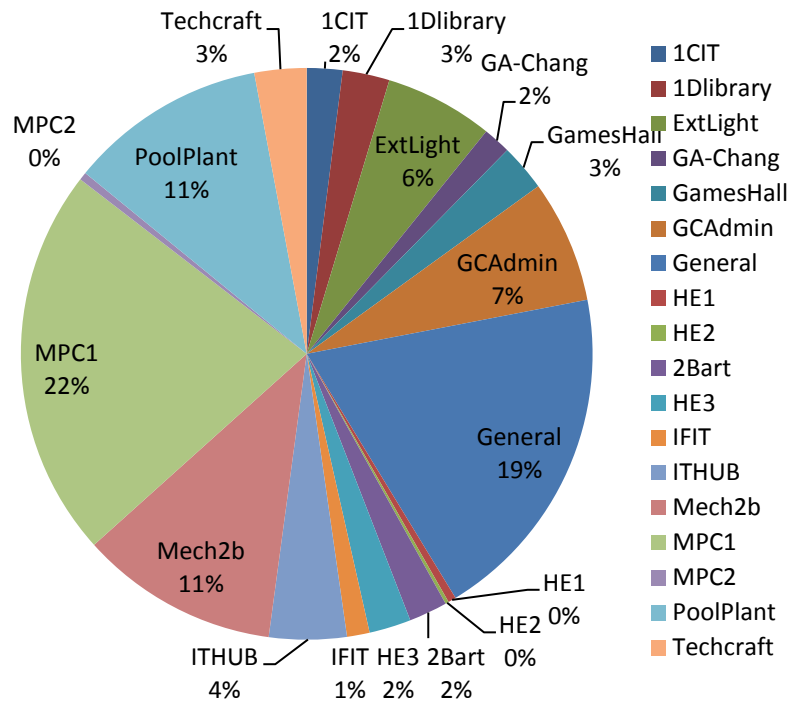


Figure 79 - Breakdown of standby power demand (by percentage) into associated distribution boards

The key distribution boards that contributed to the baseload power demand were; PoolPlant, MPC1, Mech2B, ITHub, General, GCAdmin, and ExtLight, and their demand (relative to the total baseload power demand of 31.27kW) is shown in Figure 79. Within these distribution boards, the MPC1 and General distribution boards have the largest contribution to the baseload. The boards are a mix of lighting and power (for the general distribution board), and mechanical AHU’s (for the MPC1 board). Unfortunately, not enough information is known about what the ‘General’ distribution board actually supplies power to. Interestingly, in the region of 42% of the baseload value (PoolPlant, MCP1, and Mech2B) was associated with the heating swimming pool

and pool room. The associated distribution boards provided power to numerous AHU's, the pool air handling unit and power to the boiler water pumps. The power demand for the pool during the baseload period represents 12.4kW, or alternatively 31.2kWh if taken from 00:00 to 05:30. This is substantial energy consumption for a period when the school is not being used.

B) Rise in Demand (07:30)

The main distribution boards and their percentage of total power demand were as follows; MPC1 (8.2kW, 15%), Mech2B (11.4kW, 23%), General (8.6kW, 16%) and GCAdmin (5.3kW, 10%). These distribution boards contributed in the region of 64% of the total demand. The increase in power demand relative to the baseload demand, was 1.2kW, 7.8kW, 2.6kW and 3.1kW respectively for the above distribution boards. Additionally there was increased demand present in the changing rooms and art distribution boards, with an increase in demand of 1.26kW and 1.23kW. There was also power demands monitored from two boards that had very little baseload power demand. These were the Library (1DLibrary) and the IT department (1CIT), with an increased demand of 3.9kW and 1.4kW. The rise in the Library, Changing Rooms and IT departments will be the result of the school rooms and services being switched on in preparation for the pupils. Lastly when the baseload demand and the initial rise demand were compared, it was evident that the external lighting board reduced its demand to zero by 07:30. The external lighting would only be used at night for security and illumination purposes. As the natural lighting levels were increased, the requirement for the external lighting decreased.

C) Peak Demand (10:30)

The total peak demand monitored by the distribution boards was 125kW. Three large components contributed to the demand. These were MPC2, Mech2B and General, with demands of 23kW, 15.5kW and 23kW. In relation to the total power demand at 10:30, these distribution boards accounted for 18%, 12% and 18% of demand respectively. One difference between peak demand (10:30) and both the baseload and rise in demand, was the contribution made by the 'MPC2' board to peak demand. This board supplied power to several AHU's throughout the school. The power demands for the Mech2B and General boards increased by 4kW and 14kW respectively. There were other power rises from additional distribution boards, as well as distributions that were not previously demanding power.

The boards that had an increased demand (compared with the 07:30 analysis) and the associated increase were GCAdmin (5kW), 2Bart (2kW), TechCraft (3kW), 1DLibrary (4kW) and 1CIT (4kW). The increase in demand from these distribution boards would be the result of the school used to its full potential, and classrooms being used. The additional distribution boards, and associated power demand, were IFIT (5kW), HE3 (1kW), and HE1 (3kW). The HE distribution boards are related to the home economic departments. The main equipment associated with the home economic departments, were large banks of electric cookers, and large walk in fridge/freezers. There would be additional demand from electric food appliances. The IFIT related to the IT wing of the school and represented the computer systems being used by the classes.

D) Fall in demand (17:30)

It was originally assumed that the fall in demand would be very similar to the rise in demand (in terms of associated systems). When the two disaggregated demands (initial rise and the fall in demand) were compared, as expected, several of the distribution boards contributed to both the observed rise and fall in power demand. However, it was apparent that additional distribution boards such as ‘IFIT’ and ‘HE3’ contributed to the fall in power demand but had marginal contribution to the rise in demand. The ‘IFIT’ and ‘HE3’ relate to cookers or large fridges, and computer power demand. Obviously these systems (mainly the cookers) will be used at 10:30 rather than at 07:30 in the morning, when the school is closed to pupils.

Focusing on the larger power demanding boards found in the peak demand analysis, the MPC2, Mech2B and General distribution boards demanded 3.2kW, 6.31kW and 9.5kW at 17:30. There was also a reduction in Mech2B, GCAdmin and the Library boards. This was as expected, as the school is slowly being closed to the pupils, the majority of rooms and systems would be turned off. The main decrease in demand was associated with the various air handling systems and heating systems. The rise in power demand from the GamesHall board could be the result of extra lighting being used for evening sports clubs. It was originally assumed that the peak demand would be the result of the different systems also being at peak demand. When the GamesHall power demand was investigated in Figure 78, the majority of power demand occurred from 11:30 to 14:30 and then from 18:30 to 20:30 and not at the total peak power demand.

The overall results from investigating the factors that influence the total power demand suggest that the ‘General’ distribution boards and the combined air handling boards (MCP1, MPC2, Mech2B) resulted in the largest power demands in this selected school. Other factors that contributed to the power demands were classroom specific demand such as the home economics department (HE1, HE2 and HE3) and the IT department (ITIF). The analysis also identified that the demand from the swimming pool plant remained fairly constant throughout the day, regardless of use. Clearly it is important to establish if a school has a swimming pool in order to validate the comparison as this can have an impact on power demand.

4.4 Offices

Analysing the school database demonstrated that the majority of schools consumed more energy than several of the published benchmarks. The analysis also highlighted that the daily power demand can vary between the different category of schools, as well as being influenced by the different seasons. The next stage was to determine if the analysis undertaken on the school data was also applicable to other non-domestic buildings. The half hourly power data for two office buildings were collected, as well as their construction age and total floor area. One disadvantage to this analysis was that only two buildings existed in the database, unlike the school database that contained forty-eight buildings.

One advantage of the office data over the school data was the availability of local weather data. The two studied offices had weather stations installed to monitor and record the local climate surrounding the buildings. This data was useful in determining whether or not there was a significant link between electricity consumption and key weather variables.

This section investigated the office benchmarks, the average daily and seasonal power demand profiles, and lastly how weather impacts on a buildings electricity demand.

4.4.1 Benchmarks and Comparison

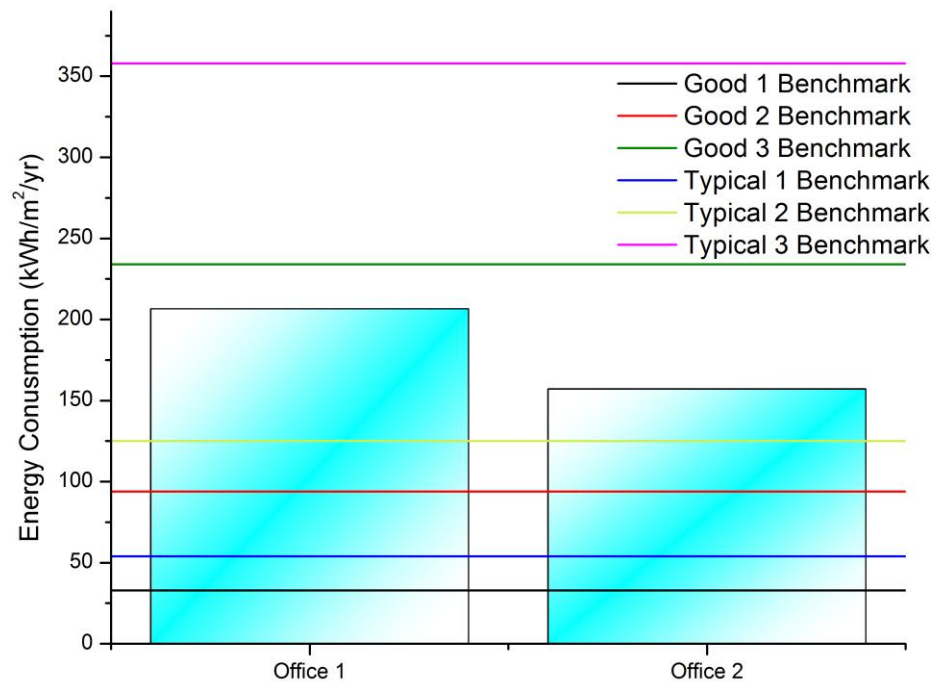


Figure 80 - Office Benchmark Comparison

The first stage of the analysis was to determine the annual electrical energy consumption of the two office buildings, and compare them with known energy performance benchmarks found during the literature review (see section 2.6). The annual consumption of the studied office (represented by the bars), and six example energy performance benchmarks (represented by the horizontal lines) is shown in Figure 80. The three ‘good’ ratings and the three ‘typical’ ratings can be found in table (section 2.6). The annual energy consumptions of office 1 was 206kWh/m²/yr and for Office 2 was 157kWh/m²/yr. The comparison against the published benchmarks indicates that the two studied offices only fall below two of the benchmarks; the ‘good 3’ and ‘typical 3’ lines.

The ‘Good 3’ and ‘Typical 3’ benchmarks were obtained from the Energy Consumption Guide (Carbontrust, (2003)), and represent a large prestigious air conditioned building. Neither of the two studied offices in this research project had the same attributes as a large prestigious building, hence why they might fall below these benchmarks. There was also a slight overlap between the ‘Good’ and ‘Typical’ ratings of offices due to energy benchmarks being used from different studies. The ‘Good 1’ and ‘Typical 1’, from the Energy Consumption Guide (Carbontrust, (2003)), represent a small naturally ventilated office. This type of building will have a lower energy consumption than a larger air conditioned office. The benchmarks ‘Good 2’ and

‘Typical 2’, were taken from a published study, however little information was provided on the what types of office (in terms of cellular, naturally ventilated, etc) were used to generate the benchmarks.

One pronounced difference between the performance benchmarks provided for office buildings and the school benchmarks (see section 2.6.2.1), was that more extensive construction details were included in the office benchmarks. For offices, unlike school benchmarks which made a distinction between primary and high schools, the Energy Consumption Guide (Carbontrust, (2003)) provided four sets of benchmarks depending on the office type and how it was constructed. The four sets of office benchmarks were; 1) naturally ventilated cellular, 2) naturally ventilated open plan, 3) air conditioned standard, and 4) air conditioned prestige.

Office 1 is a multi-storey office with a mixture of natural and mechanical ventilation, and fits into the second category of the Energy Consumption Guide benchmarks. In contrast, office 2 is a modern, built partially air conditioned building, with large windows and open spaces, and could be classed within the fourth category of ECOG benchmarks. For office 1, the benchmark for the naturally ventilated open plan office was between 54kWh/m²/yr and 85kWh/m²/yr, which is considerably less than office 1’s energy consumption. In comparison, as shown in Figure 80, office 2’s energy consumption falls below the ‘prestige’ benchmark, i.e. the fourth set of office benchmarks. The total annual energy consumption of office 2 in comparison to the ‘prestige’ benchmark could be due to either the building being considerably energy efficient, or the building lacking the same level of air conditioning as the office benchmark.

In order to further define energy consumption in the office buildings, the average daily power demand profiles were established for each office. This would allow any trends in power demand in each office to be defined.

4.4.2 Office Average Power Demand Profiles

The average daily power demand profiles for Office 1 and Office 2 were generated using same the analysis program as applied to the school power demand data. The demand profiles were normalised, i.e. expressed as W/m², in order to allow a comparison to be made against the demand profiles produced for the different types of schools.

4.4.2.1 Office 1

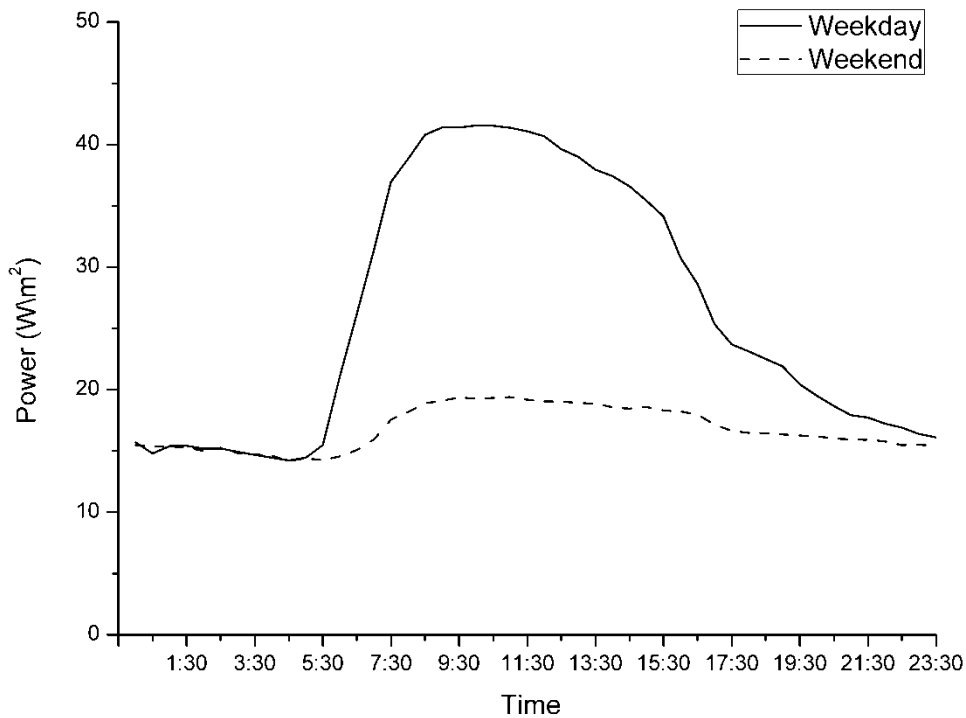


Figure 81 - Office 1 Average Daily Power Demand Profiles

The office remains at baseload ($14.4\text{W}/\text{m}^2$) until 05:30, when the power demand increases to $41.5\text{W}/\text{m}^2$ by 09:30. The demand plateaus until 12:00 when the demand slowly decreases in three identifiable stages. These stages are from 12:30 to 15:30, 15:30 to 17:30 and 17:30 to 00:00. The first to decrease in power demand will be the result of a reduced lighting or heating requirement. The second, and quicker, drop in power demand could be the result of certain sections of the building closing as the end of the working day approaches. The third decrease in power demand returns the power demand of the building from $25\text{W}/\text{m}^2$ to baseload over six hours. The slow decrease in demand could be the result of staggered employee working hours, lighting being slowly switched off, and perhaps an automatic shutdown of worker computers.

The weekend power demand had the same baseload at the weekday average demand profile, suggesting that there is little change in how the buildings systems are used between the weekdays and weekends over this time period. There is some active power demand during the day at the weekend occurring from 05:30 to 17:30. It was most likely that this weekend power demand was the result of the public enquiry sections of the office being open, as opposed to the whole office being open. However, it is also possible that there could be limited office use at weekends. The peak power demand was $19.4\text{W}/\text{m}^2$ and occurred at 09:30, and the power demand varied from this value slightly 17:00. The power demand then decreased back to baseload over a period

of several hours. If it is assumed that this active weekend power demand was the result of the public offices, it would likely also occur during weekdays, making a contribution to the total power demand of the office. If this was the case, the office open at the weekends would account for 5W/m^2 , or 18% of total peak demand of these public buildings.

The impact of the seasons on the power demand profile from Office 1 was also examined (Figure 82).

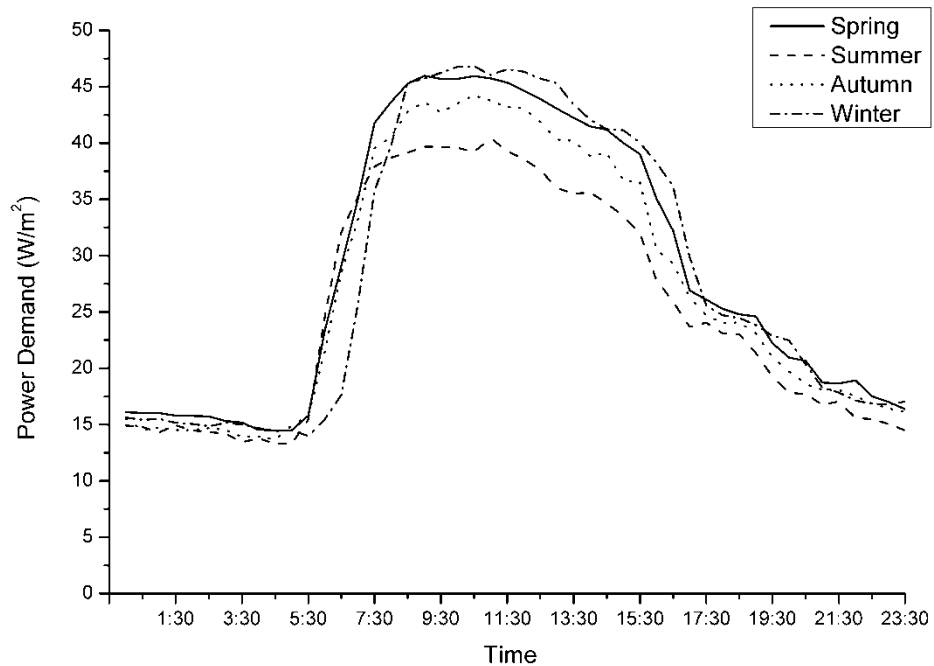


Figure 82 - Office 1 Average Seasonal Power Demand Profiles

The results suggest that the seasons have modest impact on the power demand profiles of Office 1. The most pronounced difference was the summer profile with its lower peak power demand. The summer has a peak power demand of 40W/m^2 , whereas spring, autumn and winter had peak demands of 45W/m^2 , 43W/m^2 and 46W/m^2 . Similarly with schools, the lower summer peak demand could be the result of a lower requirement for artificial lighting and less use of heating pumps.

In addition to a decrease in peak power demand in summer, a more prominent decrease in demand from 11:30 onwards was observed between summer and winter. Several reasons could account for this earlier drop in power demand in summer. Systems contributing to the power demand could be switched off earlier, or switched off at a greater rate, or the total number of active systems may be less in summer than winter. Interestingly, the unknown/unidentified systems are active from 05:30 onwards there appears to be a lag phase in winter with the rise in demand being delayed from 05:30 in spring, summer and autumn, to 06:30 in winter. This is a surprising finding, as

it would be expected that if anything, power demand would occur earlier in winter than the other seasons.

4.4.2.2 Office 2

The average power demand profiles for Office 2 are shown in Figure 83.

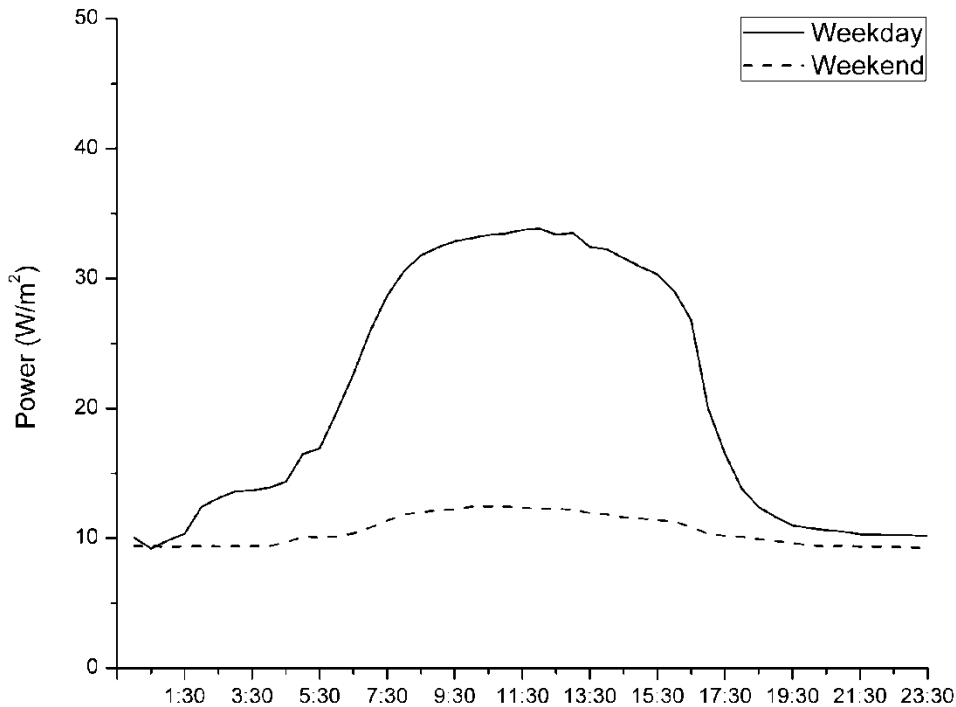


Figure 83 - Office 2 Average Power Demand Profiles

The baseload of office 2 was 9.8W/m^2 for both the weekday and weekend profiles. The weekend profile had a slight rise in power demand starting from 06:30, reaching a peak demand of 12W/m^2 by 10:00, and returning to standby at 20:00. The slight rise in power demand, only 2W/m^2 off the baseload value was most likely due to limited office weekend usage. Such a small demand would indicate that only a small proportion of the office was being used. On further analysis, it was discovered that there was a small office that dealt with customer enquiries that was open on Saturdays (as well as during the week).

The weekday profile had an initial increase in power demand that appeared staggered or stepped. It was found that the decrease in power demand of office 2 was stepped/staggered, whereas the initial rise of office 1 had a fairly smooth increase.

The impact of the seasons on the power demand profile for Office 2 was examined (Figure 84).

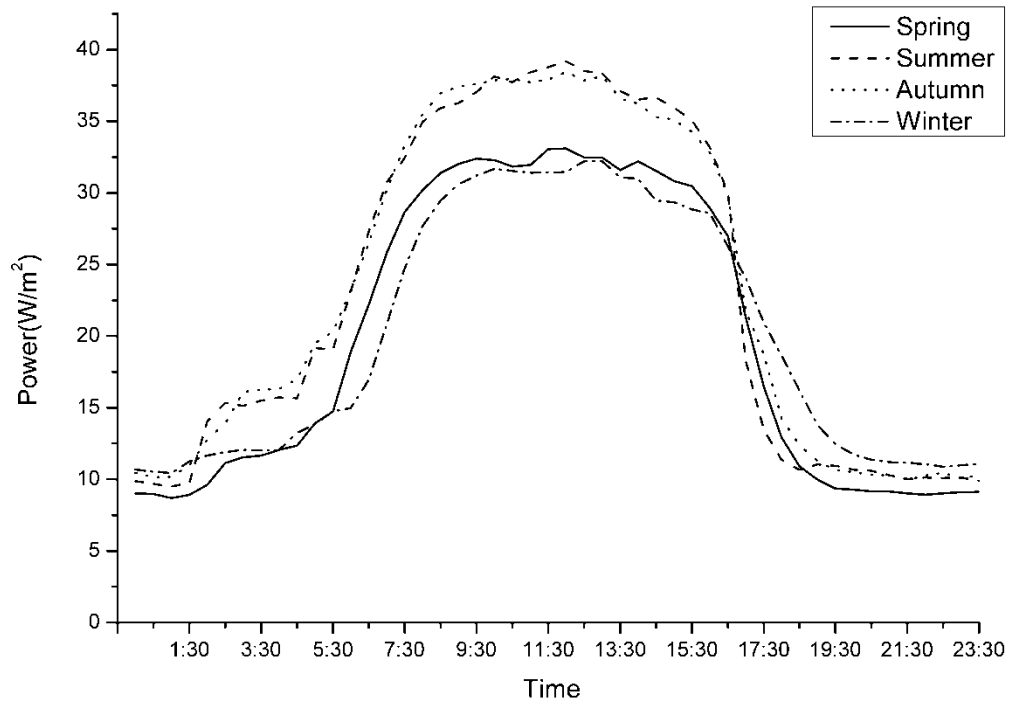


Figure 84 - Office 2 Seasonal Power Demand Profiles

The power demand profiles clearly demonstrate that summer and autumn have a higher peak power demand than spring and winter. This difference is in the region of $7\text{W}/\text{m}^2$. This finding is in contrast to the seasonal impact on power demand of Office 1, in which summer resulted in a lower peak power demand than winter. This difference is most likely due to office having air conditioning (or at least some form of air conditioning). The seasons appeared to have a small impact on the baseload power demand, with spring having the lowest value ($9\text{W}/\text{m}^2$) and winter and autumn having the highest baseload value at $10\text{W}/\text{m}^2$.

The step-wise rise in power demand was still evident with each season, although shifts in the magnitude of the rise were apparent from 01:30 to 05:30. Autumn had the largest demand at 05:30 with $20\text{W}/\text{m}^2$ with winter having a demand of $14\text{W}/\text{m}^2$.

There was also a lag period in the rise in power demand. If the power demand of $25\text{W}/\text{m}^2$ is taken as a reference point, this was achieved at 05:30 for autumn and summer, where as spring it was achieved at 06:30 and winter 07:30.

The impact on the power demand profiles for offices and schools due to the seasons indicated that the weather was also likely to have an influence. Fortunately, weather information was collected and available in the office datasets (but not schools). The two weather variables studied were external temperature and global solar radiation.

4.4.3 Weather Introduction

The office data was also analysed in conjunction with each offices surrounding microclimate. Key weather variables, such as outdoor temperature, indoor temperature, rain fall rate and global solar radiation, were collected and recorded. The following sections aim at determining if there is a link between each office’s power demand, and selected weather variables.

4.4.3.1 Impact of External Temperature on Power Demand

The first stage of the weather analysis was to plot the power demand, in kW, against the outdoor temperature.

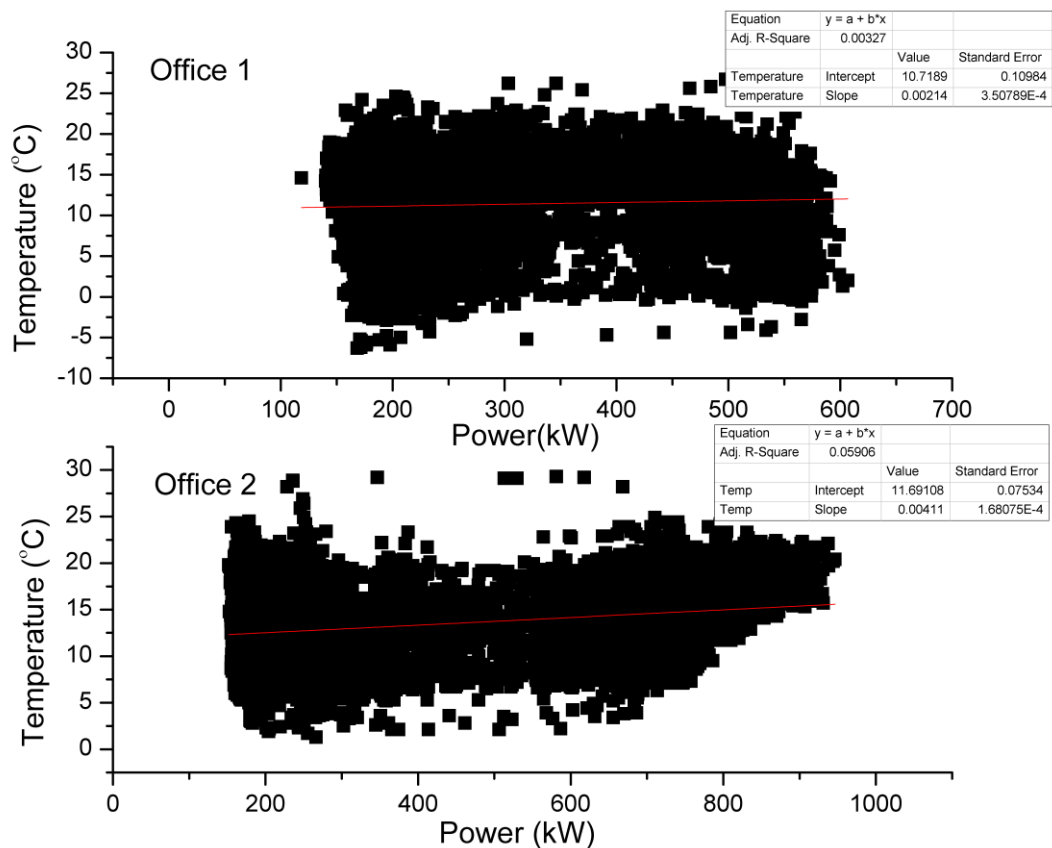


Figure 85 - Temperature versus Power For Office 1 and 2

Plots were created to determine if any trend existed between the power demand of a building (Office 1 and Office 2) and the external temperature surrounding the buildings. In the previous sections the assumption was made that the heating systems would be used more frequently in winter than in summer to compensate for lower external temperatures in winter. The corresponding scatter plots of temperature against power demand, suggested an unclear direct link between these two variables (Figure 85). This lack of relationship between temperature and power demand was also confirmed using linear regression analysis. The residual square (adjusted), or R², for

Office 1 was 0.00327 and for Office 2 0.0596. The low R^2 values for both plots suggested that there was little trend (linear) between the outdoor temperature and the building’s power demand.

The failure to demonstrate a link between outdoor temperature and power demand is counter intuitive. However, the failure to detect a trend with these two variables may be due to the fact that the power demand data set comprises of data captured throughout the year. As the seasons appear to have an effect on power demand, combining data from the four seasons may mask a relationship between external temperature and power demand. Lower demand in the summer, may skew the data from showing a relationship between colder external temperatures (autumn/winter) and power demand. Further analysis was undertaken using heating periods (primarily winter for office 1) and cooling periods (primarily summer for office 2) to determine if a relationship existed between temperature and power demand under these conditions.

The results from this analysis are highlighted in Figure 86, with linear regression applied to both office buildings.

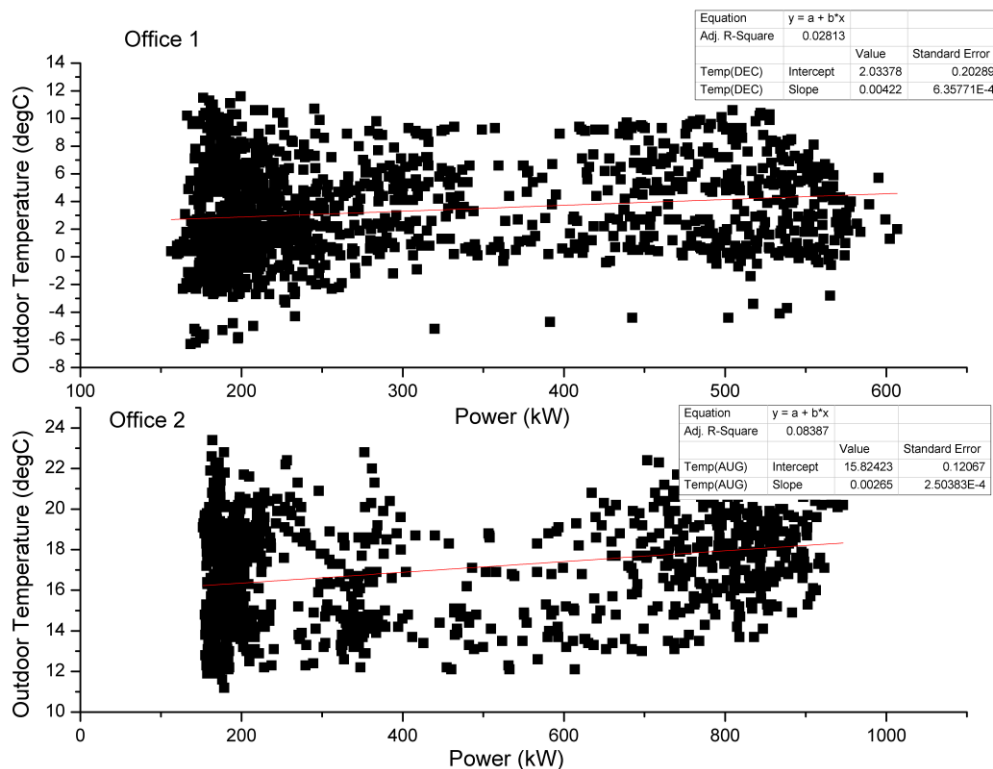


Figure 86 - Analysis of Temperature and Power with Selected Data

Restricting the data to the heating and cooling periods reduced the number of data points (from 9000 to 1400). Restricting the datasets to the heating and cooling periods resulted in a marginal improvement in the linear regression residuals (R^2) from 0.0037 to 0.028 for Office 1 and 0.0596 to 0.0837 for Office 2. However, although the

heating system appears to have more of an impact on power demand in winter for office 1 and the cooling system in summer for office 2, their impact does not appear to be significant with respect to the increase in power demand observed in these offices.

The next variable investigated was the global solar radiation (or external light levels). The global solar radiation levels will be higher in summer than in winter. Thus in winter demand for artificial lighting would be higher than in summer. The impact of the global solar radiation on power demand was examined.

4.4.3.2 Impact of Global Solar Radiation on Power Demand

The scatter plot for power demand versus global solar radiation is shown in Figure 87

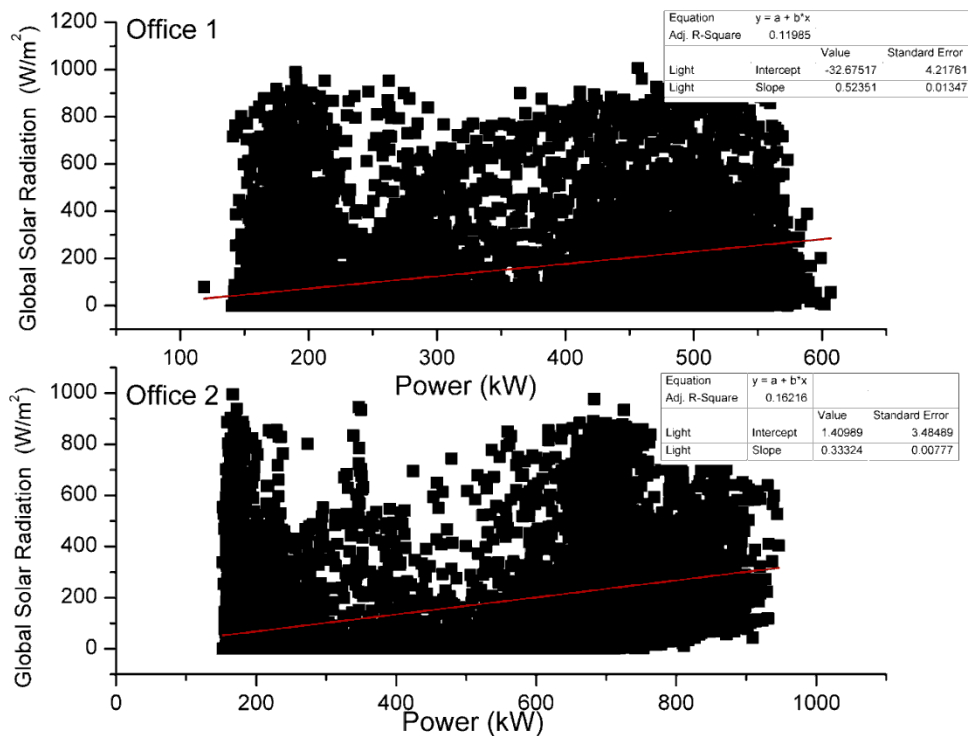


Figure 87 - Global solar radiation versus Power for Office 1 and Office 2

As with external temperature, there appeared to be little relationship between global solar radiation and power demand in both office 1 and 2. The lack of relationship was confirmed with linear regression analysis. The linear regression analysis residual (R^2) was 0.12 for Office 1 and 0.16 for Office 2. Overall, although the results for temperature and global solar radiation did not confirm a significant relationship with power demand, global solar radiation appeared to have a stronger relationship than external temperature.

A sub-analysis was undertaken to confine the datasets to the periods where the contribution of artificial lighting would be more pronounced, i.e. winter. The data from

December was analysed with linear regression for both offices using this restricted dataset.

The global solar radiation versus power demand for both office buildings using the restricted data set is shown in Figure 88.

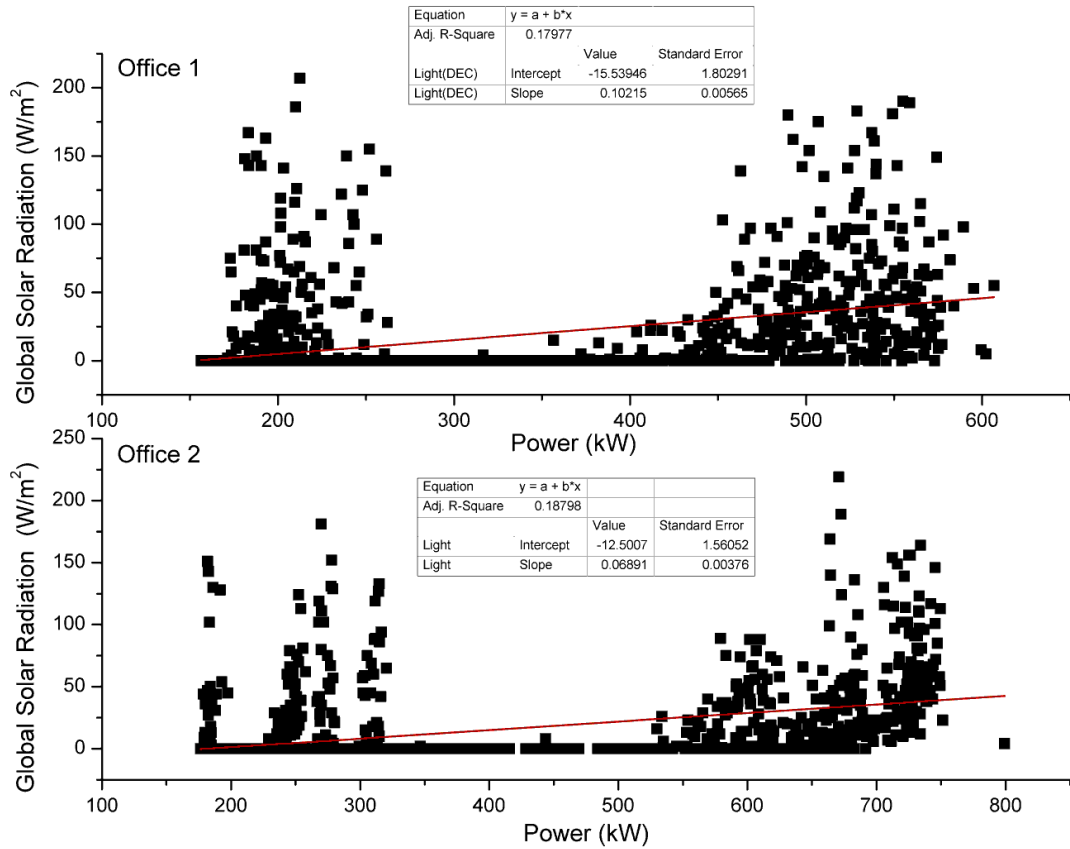


Figure 88 - Analysis of Light Levels and Power for the reduced dataset

The linear regression analysis failed to demonstrate a significant relationship between the global solar radiation and power demand for offices using this restricted dataset. Thus, suggesting that there was not a clear relationship between these two variables. Although there appeared to be an increased relationship between global solar radiation and power demand in winter for both offices, this increase was only modest and at best could be regarded as a trend. The linear regression residuals (R^2) increased from 0.12 to 0.18 for Office 1 and 0.16 to 0.19 for Office 2.

Analysis suggests that power demand profiles vary over a 24 hour period and are influenced by various extents by the seasons. The previous section dealt with the impact of the demand of systems primarily using electricity to function. In this following section, the impact of systems that consume gas as the primary source of energy will be discussed.

4.5 Thermal Analysis

If a building has electric space heating or electric storage heaters, then the heating component of energy use has been analysed during the electrical demand analysis. However, gas or fossil fuel thermal systems are more common in non-domestic buildings, as well as domestic buildings. To fully understand energy use patterns of buildings, all areas of energy consumption have to be accounted for. This section discusses thermal energy consumption, and investigates whether the available gas usage data can be analysed using the same methodology as the electrical data. This section addresses several key stages of analysis; a) analysing a sample day, b) determining the differences between a weekday and weekend profile for a sample school, c) determining any seasonal variation of a sample school and lastly, d) comparing the average/seasonal profiles to other schools.

4.5.1 Example Gas Demand Profile

In order to determine how gas (or fossil fuel) is used within a building, it is important to analyse daily gas demand profiles, in the same way the power demand profiles were analysed. The thermal demand over a 24 hour period for a sample school day (from TS1) is shown in Figure 89. This profile represents an actual day's gas usage, and not an average demand profile generated from a year of data.

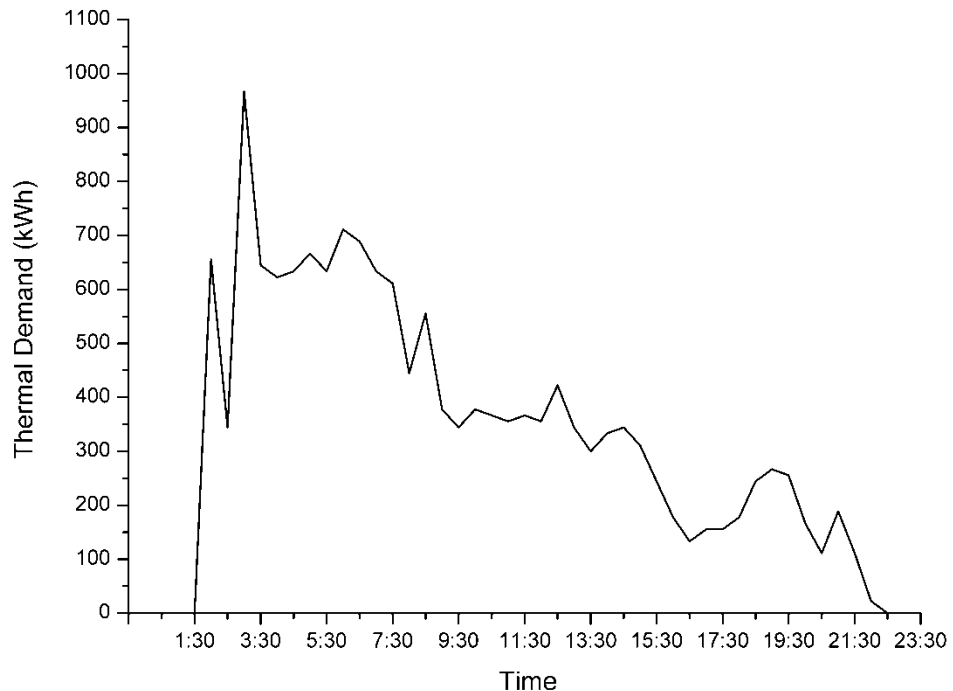


Figure 89 - Example Gas Demand Profile

Key terminology used to discuss the power demand profiles, such as the baseload and peak demand, can also be applied to the gas usage analysis. The baseload demand was 0kWh and the peak demand was 966.6kWh. There appears to be several sharp peaks occurring at various time points throughout the day. The initial sharp peak starts at 01:30 and followed by a second sharp peak at 03:30. The peak demand appears at 05:30, followed by an overall decline in gas demand until 22:30. However sporadic sharp peaks occur from 08:30 to 22:00.

The analysed sample day dataset represented a sample weekday. The demand for gas, as with the demand for electricity, would be less at the weekend than weekdays. The average gas demand at a weekend and weekdays is shown in Figure 90.

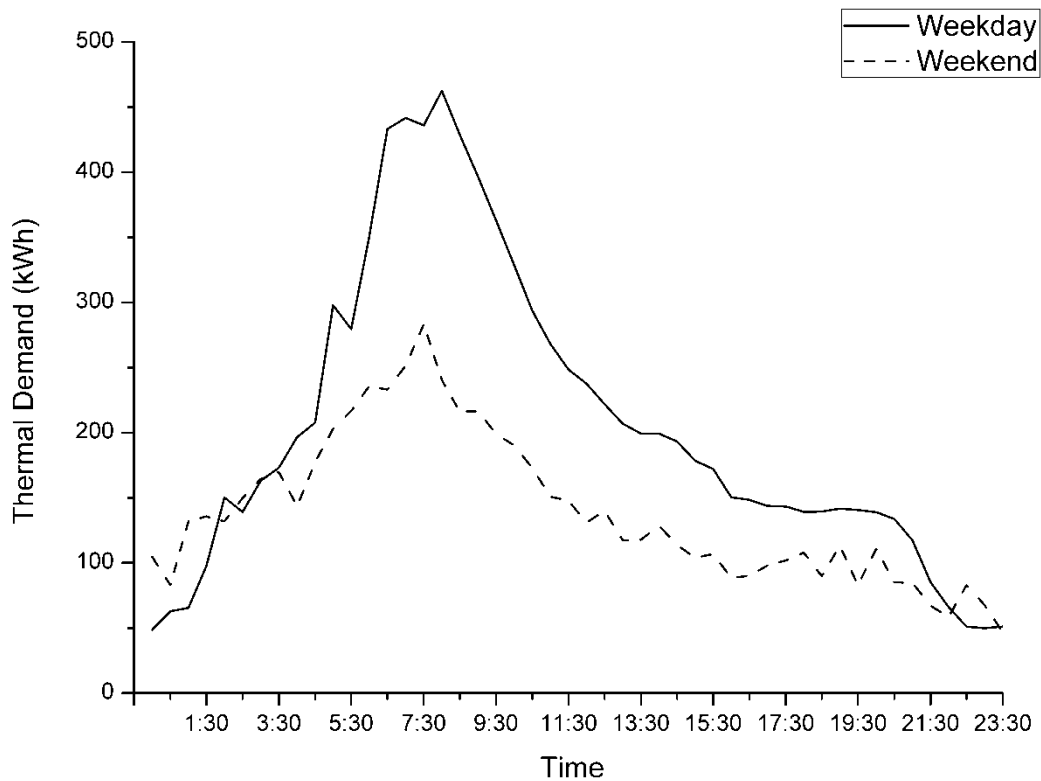


Figure 90 - Average Gas Demand Profiles

The overall gas demand profile was similar for the weekdays and weekends, with the exception of the extent of gas usage; greater usage at weekdays relative to weekends. The peak gas demand was 462kWh at 08:30 at weekdays and 283kWh at the weekend. The baseload values were 46.5kWh for the weekend and 48.7kWh for the weekday.

The gas demand profiles indicate a difference between the weekdays and weekends. In addition, the difference was observed in the average demand profile and the sample day demand profile (baseload, peak and general shape). An analysis of the

impact of the seasons on the average gas demand profiles was undertaken to determine if the seasons could explain the differences between the average gas profile (Figure 90) and the sample day profile (Figure 89).

4.5.2 Seasonal Comparison

The impact of seasons on the weekday gas demand profiles from thermal school 1 (TS1) is shown in Figure 91.

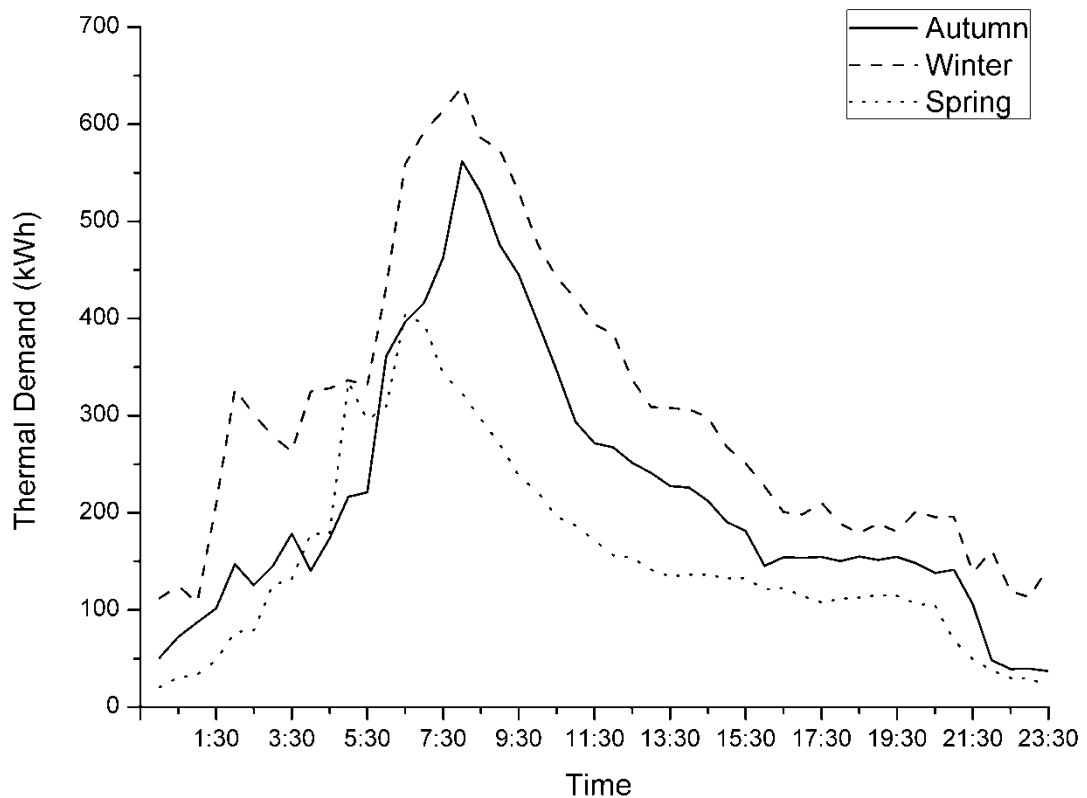


Figure 91 - Average Seasonal Profiles for Thermal School 1 (TS1)

One issue arose when calculating the average seasonal gas demand profiles. The gas usage data supplied only covered nine months of the year, and as a result the average summer demand could not be calculated. The profiles demonstrated in Figure 91 represent only the autumn, winter and spring. However, even without the summer demand profile, the results indicated that there was significant seasonal variation in the gas demand.

The seasons appear to have an impact on the baseload, with winter having a greater impact than autumn or spring. The respective baseload values were; 107kWh, 36.95kWh and 20.6kWh. A similar rank order of winter (638kWh), autumn (561kWh), and spring (403kWh) was observed for peak gas demand, although the time for achieving peak demand varied as a function of the seasons. In winter and autumn, the peak demand was achieved at 08:30, whereas in spring it was achieved at 06:30.

In contrast to the other seasons, winter appeared to result in a large increase in gas demand from 0:30 to 03:30. This achieved a gas demand of region of 325kWh over this time period and represented approximately 57% of the peak gas demand for that day. The seasons also appeared to have a marked effect on the decrease in gas demand. In spring, the fall in demand reached a plateau from 13:30 to 20:30 with a rapid fall from this time to 23:30. Although winter demand for gas appeared to fall at a similar rate as with spring, by 23:30 gas demand was still evident with a value of 119kWh.

The final step in the gas usage analysis was the creation of average gas demand profiles for a selection of schools, to establish if trends existed within the schools.

4.5.3 Average Profiles

The previous sections within this chapter have discussed the analysis of a sample thermal day, the average profiles and how seasonal impacts on a school’s gas demand. To determine if there were any trends within the types of school, the average daily demand profiles were calculated for each of the schools within the thermal database. For an equal comparison, the gas data was normalised by the corresponding floor area of the respective school.

The average weekday gas demand profiles for the five schools are shown in Figure 92.

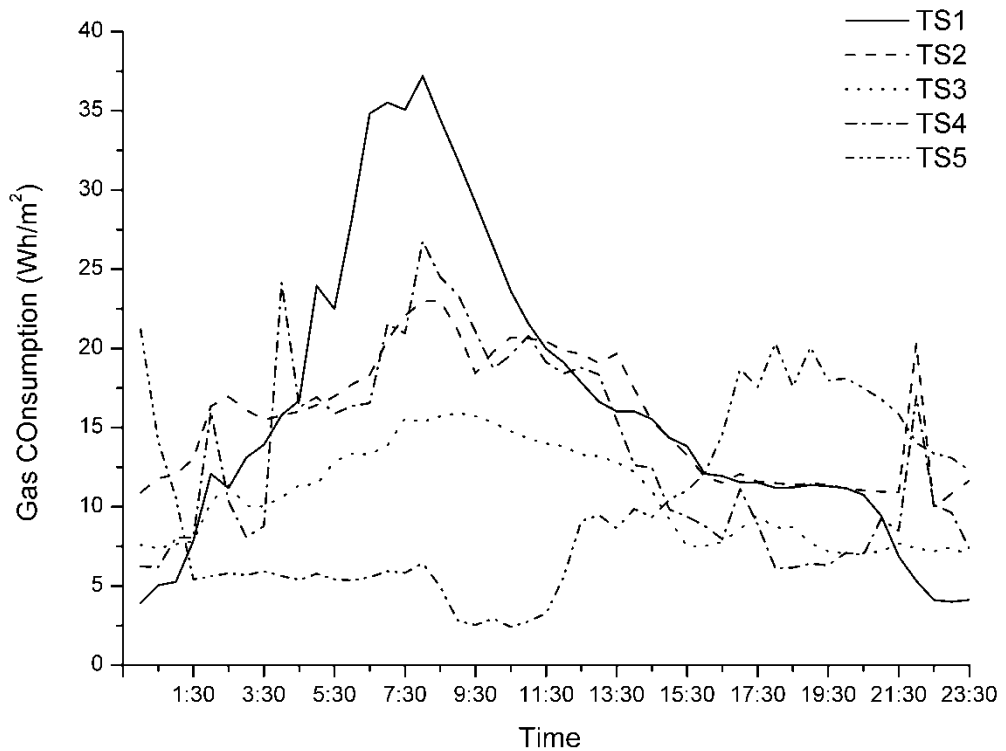


Figure 92 - Average Weekday Gas demand for all five schools (Thermal Schools)

Four of the schools (schools TS1, TS2, TS3 and TS4) demonstrated an overall similar gas demand profile although the magnitude of the demand differed between the five schools. Peak gas demand occurred between 06:30 and 09:30 for the four schools varied from 15Wh/m² to 39Wh/m². A marked difference in baseload values was observed, with values ranging from 3.9Wh/m² to 10Wh/m². Two sharp peaks were observed in schools 2 and 4 at 22:00. In contrast to the similar gas demand profiles for schools TS1-4, the fifth school (TS5) displayed a unique gas demand profile that appeared to be an inversion to the other school's demand profiles. The baseload value 00:30 was 5.4Wh/m². Instead of demonstrating the expected rise in gas demand after this time point, gas demand actually fell reaching a peak fall in demand of 2.5Wh/m² at 09:30 (peak demand is achieved at this time in the other schools). A subsequent rise in gas demand occurs from 09:30 onwards, and reaches a peak demand of 2.3Wh/m² by 18:00. The weekday gas demand profiles for this school appears to be out of synch with the other schools.

4.6 Initial Analysis Conclusion

This chapter discussed the initial analysis of the various energy databases to provide a firm foundation for further analysis. The chapter first described the analysis of the school electricity database, focusing on annual energy consumption. By introducing several factors, such as floor area, construction age and school type, the impact of these factors was determined. Additionally, a comparison was made between the school energy consumptions per category against published energy performance benchmarks to gauge the energy efficiency of the collected database. The results revealed that the collected schools had high energy consumption, than the published benchmarks, and further reinforced the issue of how representative current benchmarks are.

Chapter 4 also discussed the analysis of three selected school (one for each category of school), but at a half hourly time resolution opposed to an annual resolution. This allowed an insight into how power demand varied at between weekdays and weekends, as well as between each category of school. Additionally, the seasonal impact on the power demand of each chosen school was investigated as well as the differences of seasonal impact between each school. A key finding was that the schools shard a similar demand shape. Lastly the analysis investigated distribution board power demand data, to determine which systems were the driving factors in the standby, initial rise of power demand, peak power demand, and fall in power demand. The distribution

board data allowed a more detailed view of how power was used in a school in comparison to the total metered data.

The chapter then focused on the analysis of the office electrical data, investigating the annual energy consumption against the known office benchmarks, as well as investigating the power demand profiles. Although the office electricity database consisted of only two buildings, it offered a comparison between an older constructed office, and a new, low energy office. In addition to the electrical data, corresponding weather data was made available. Both outdoor temperature and global solar radiation were compared with the electricity data, resulting in no significant trend between the variables.

Lastly, the chapter investigated half hourly thermal demand profiles, and identified the differences between weekday and weekend demand, as well as the seasonal differences. A key stage in the thermal demand analysis was investigating determining that there was a similar demand shape present in four of the five studied thermal schools.

The initial analysis identified the driving factors of energy consumption/power demand, as well as key differences between the power demand of schools and offices, as well as weekday, weekend and seasonal impact. The conclusions gained, determined that the similar shape of the school power demand could be generalised, providing several factors were accounted for. The gained conclusion provided a firm foundation for the more in-depth analysis discussed in the following chapter.

Chapter 5 RESULTS: GENERIC PROFILES

The previous chapter dealt with average power demand profiles obtained in the collected database. This chapter extends the analysis to individual school power demand profiles to determine if the generation of generic or ‘typical’ demand profiles is possible.

5.1 Normalised Power Profiles – Inclusion of Floor Area

The first normalisation factor considered was school total floor area.

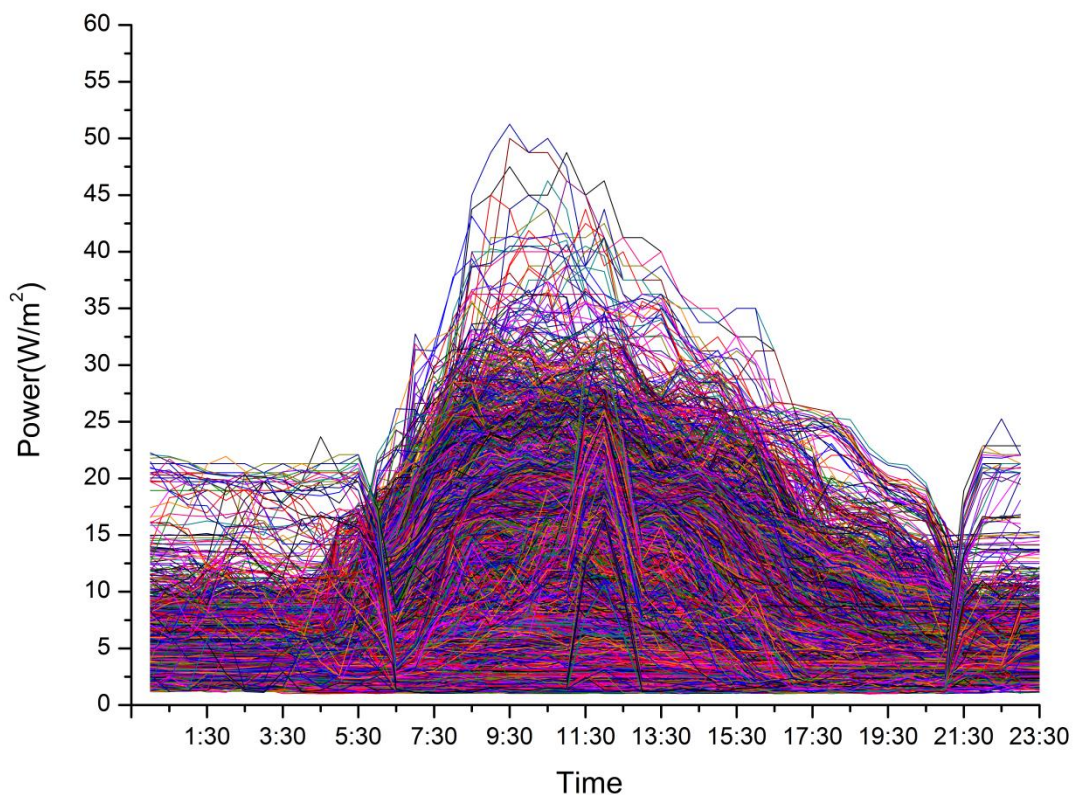


Figure 93 - Normalised Power Demand Profiles

The individual power demand profiles for each school over a 24 hour period, is shown in Figure 93. Two datasets were considered, a) inclusion of holiday data, and b) exclusion of holiday data. With inclusion of school holidays, approximately 800,000 points required analysis, whereas with exclusion, this number fell to 600,000 points. In order to plot this level of detail, the data was sampled (with a sample rate of three), to produce an output that contained over 200,000 points. Each time index (00:00,00:30 etc) was sampled at a rate of three, resulting in every third day to be selected and added to the new sampled dataset. The plot for all school demand profiles over a twenty-four hour period and normalised by floor area is shown in Figure 93. As discussed in the

methodology section, further normalisation using weather or pupils is not necessary at this stage (see Section 3.4.4).

With the normalised data (Figure 93), three noticeable demand profiles were evident. The first two are consistent with the non-normalised data, although the broad peak is more defined.

Assuming that the three profiles identified in the normalised data (Figure 93) correspond to unchanging demand, broad peak and sharp peak then the power demand for each profile can be defined. The assumption is also made, that each of the three profiles will have a corresponding baseload and peak demand.

The unchanging power demand has a baseload ranging from 0-5W/m², and by definition has no peak demand value. The broad peak demand has a baseload from 0-10W/m², and a peak demand of 24W/m². Lastly the sharp peak demand has a peak demand over 90W/m².

Linking power demand profiles to floor area, appears to generate a more ‘normalised’ power demand profile that makes it possible to compare between the sources of demand data.

The impact of removing weekend power demand data on the corresponding power demand profiles for the schools previously analysed, was assessed.

5.2 Weekend Removal

The normalised power demand profiles, excluding weekend data, are shown in Figure 94.

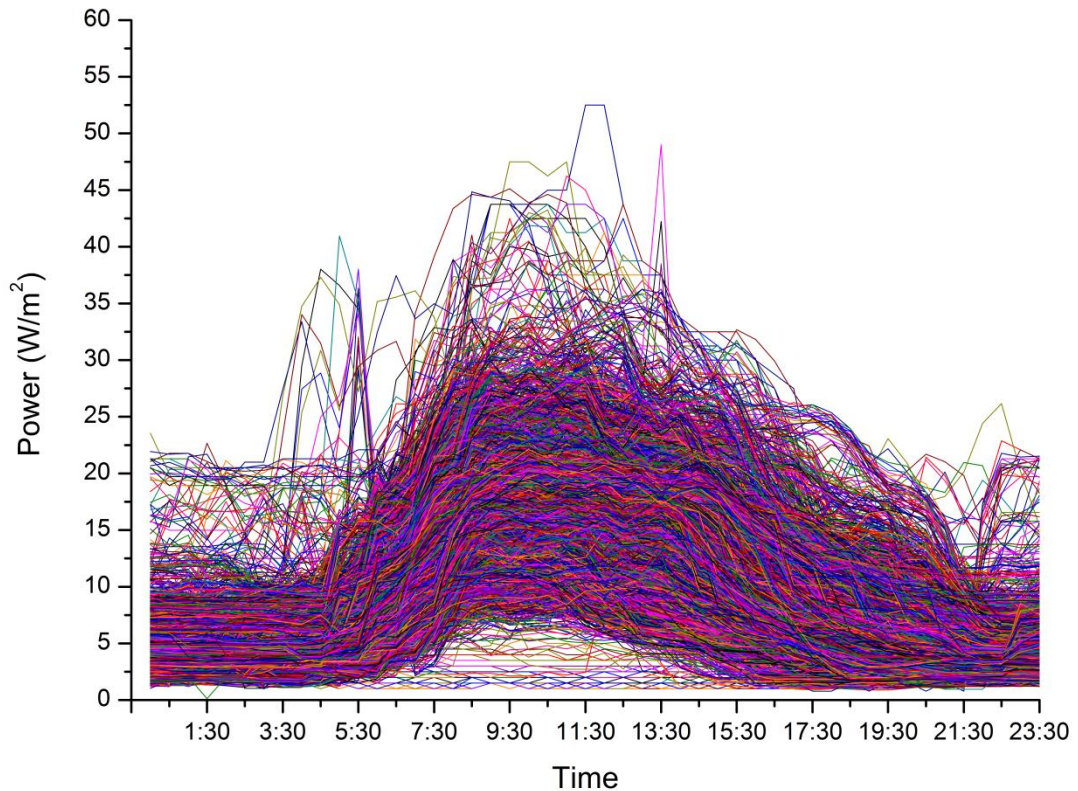


Figure 94 - Normalised Profiles with Weekends Removed

A confounding factor with weekend data, is that schools may use power at the weekends differently. Some schools may have pronounced weekend power demand due to activities, such as sport, whereas other schools, may have minimal power demand. Thus removal of the weekend data will remove this variable and should lead to a more ‘generic’ profile.

The plots of each school’s power demand, minus the weekend days, are shown in Figure 94. One difference observed between Figure 93 and Figure 94 is that following removal of weekend data, the broad peak in power demand appears to be more pronounced. This is evident between 05:30 to 14:00.

Overall, removal of the weekend power demand profiles, did not have a significant impact on peak demand (as expected), but did appear to remove some of the variability, such as sharp peaks and the unchanging demand.

An assessment of the category of schools on the normalised power demand profiles was undertaken to determine if differences existed between the types of schools.

5.3 Profiles by Category

The normalised power demand profiles, over a 24 hour period by school type is shown in Figure 95.

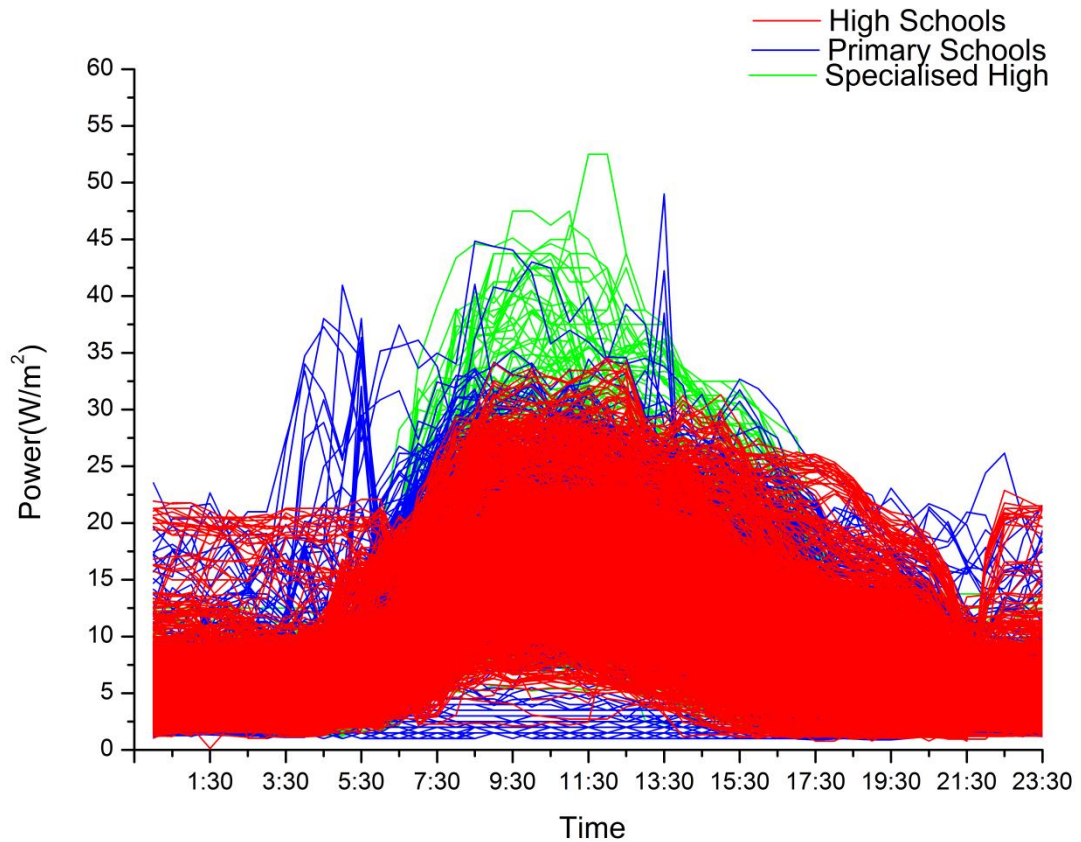


Figure 95 - Power Profiles by Category

Three school categories were used; a) high schools, b) primary schools, and c) specialised high schools. The demand profiles for each category/type can be identified in Figure 95. The high schools, primary schools and specialised schools are represented by red, blue and green coloured profiles respectively.

Overall, it appears that there is more consistency in the normalised demand profiles of high schools, in comparison to primary schools or specialised high schools. Several distinct sharp and broad peaks were evident. Furthermore, the number of sharp peaks was more readily identifiable with high schools than the other two categories.

The normalised demand profiles for each school category will be discussed in turn.

5.4 Optimisation of the Datasets.

Six schools were excluded from the database. The aim was to restrict heating to gas (or other fossil fuels), and to exclude electric heating (both space and storage). This was due to electric based heating systems (both storage and space) significantly impacting on the power demand profile. In contrast, gas/fossil fuel based heating

systems only have a slight impact on the power demand (in terms of electric pumps, and some AHU use). In addition, demand profiles that showed marked variation from the derived ‘typical’ profiles, were also excluded. In total five schools were excluded from analysis; school 4, 14, 17, 40 and 43. Each school will be discussed in turn.

5.4.1 School 4; non-‘typical’ demand profile (Figure 96)

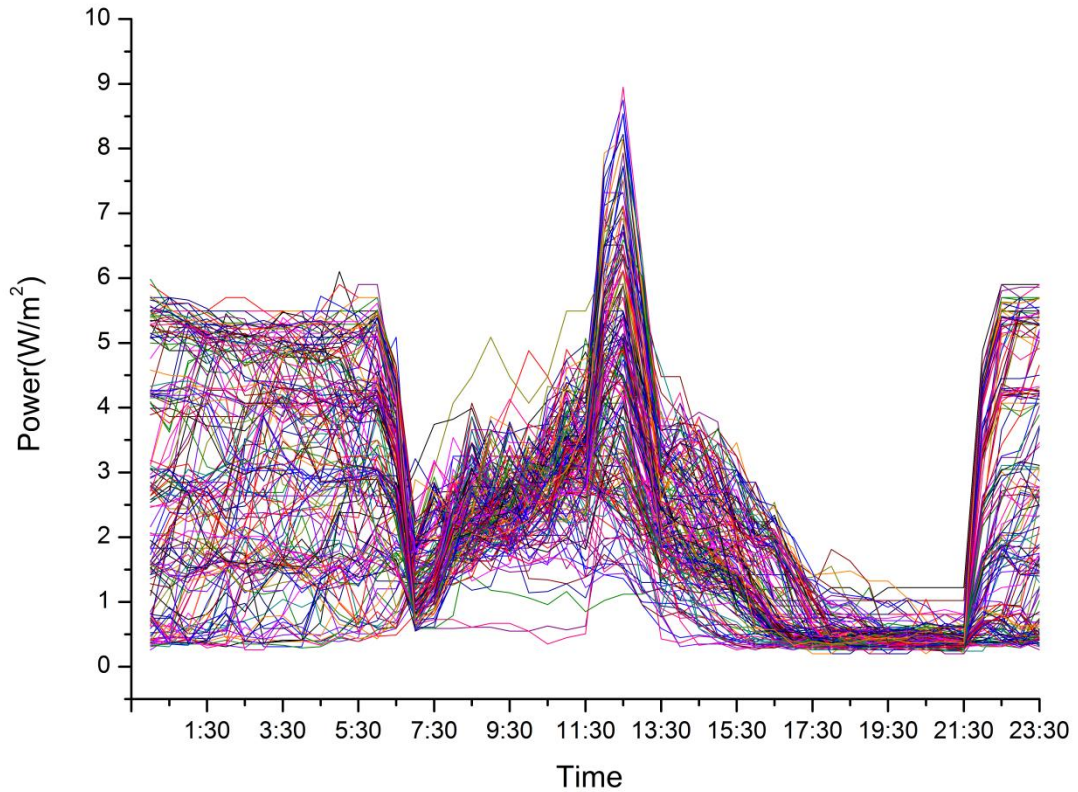


Figure 96 - Power demand Profiles for School 4

School 4 has a high baseload (relative to the peak demand of that school) of around $6\text{W}/\text{m}^2$ that falls to $1\text{W}/\text{m}^2$ at 07:00. The demand then rises to a high peak of $8\text{W}/\text{m}^2$, where the demand falls until 21:30. The power demand then increases back to the baseload of $6\text{W}/\text{m}^2$. Although the baseload would normally be considered as the lowest power demand, in school 4’s case, the unchanging demand that occurs throughout the early morning and later evening can be classed as the baseload. There appears to be several groupings of standby, starting at $1\text{W}/\text{m}^2$ and incrementing by $1\text{W}/\text{m}^2$ up to $6\text{W}/\text{m}^2$. Further analysis or monitoring the distribution boards would determine why this school has a layered baseload, and a unique shape of profile. Possible reasons for the changing baseload could be linked to a system within the school that has a varied power demand throughout the year.

5.4.2 School 14; Electric Heating (Figure 97)

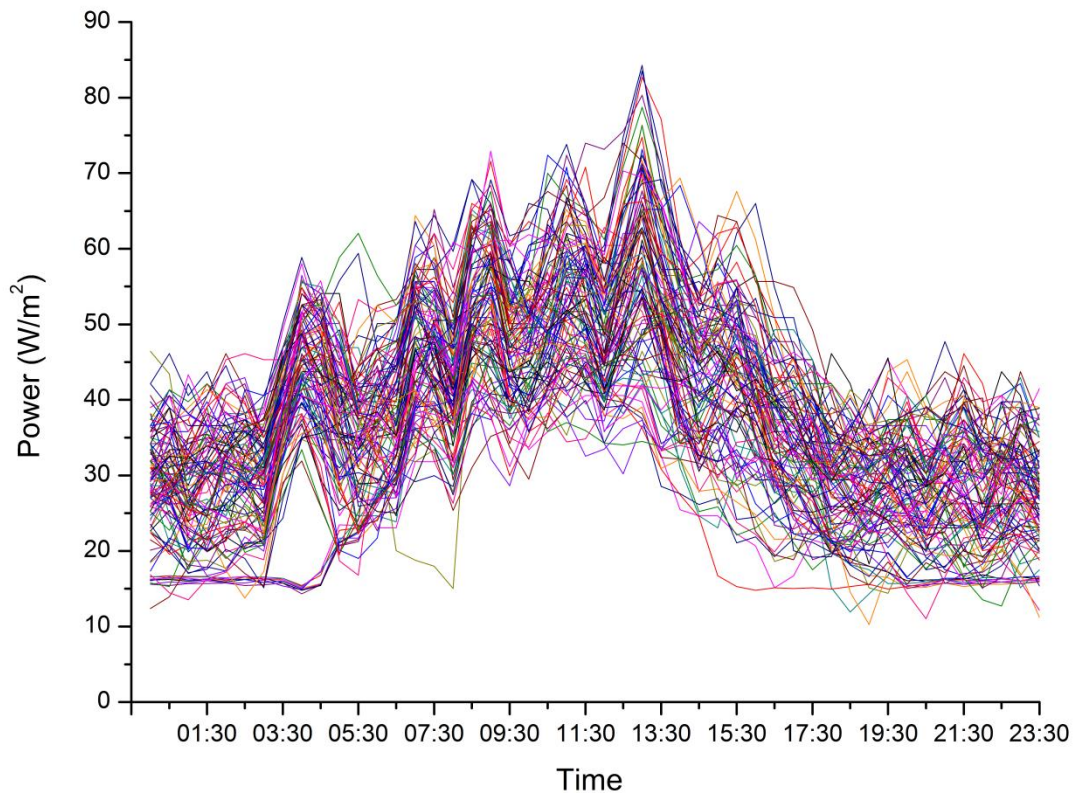


Figure 97 - Power Demand Profiles for School 14

The demand profiles for school 14 appeared to have a profile similar to a broad peak, however it has repetitive sharp peak demands occurring throughout the profile. The baseload of school 14's demand profiles is between 15W/m² and 40W/m² and the peak ranges from 30W/m² to 80W/m². The primary, or larger sharp peak demands occur during the morning and early afternoon, with very sharp peaks occurring during the evening and early morning. This could be associated with electric space heating, with the system being used early on in the morning to heat the school throughout the day to maintain the desired temperature, and is used less from 14:00 onwards.

The sharp peaks have duration of approximately 1.5 hours, and vary in power demand (~20W/m²). The building appears to have a similar demand profiles other schools in terms of a rise in power demand in the morning (04:30) to a peak demand (11:30) and a return to baseload (18:00). The unique profile shape of school 14 was a combination of the typical broad peak in power demand (due to rise and fall of small power) and the repetitive sharp peak demands (associated with electric heating).

5.4.3 School 17; Electric Space Heating (Figure 98)

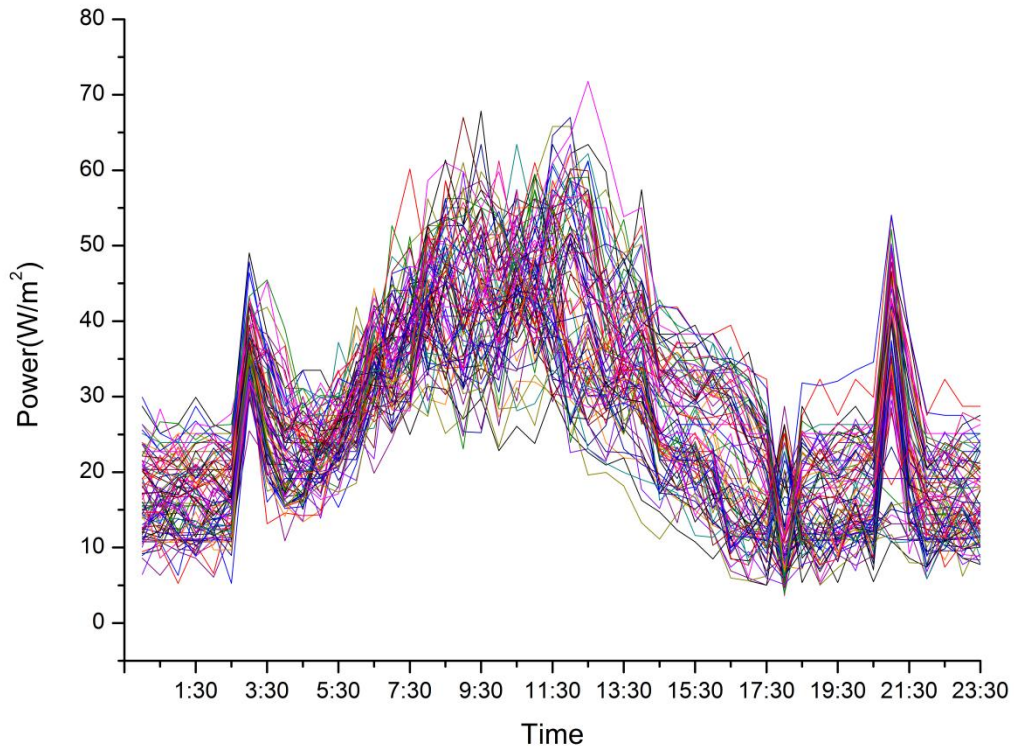


Figure 98 - Power Demand Profiles for School 17

The power demand profiles for school 17 have similar traits to the other schools that incorporated a form of electric heating (space/storage). Two main demand shapes were identified with the demand profiles presented in Figure 98; a broad peak and two distinct sharp peaks. The two sharp peak demands occur from 02:30 to 04:00 for the first peak and from 20:30 to 22:30 for the second. Both sharp peak demands have a duration of 1.5 hours, and have peak demand between 48W/m^2 to 54W/m^2 . Seasonal analysis revealed that a 15W/m^2 difference, in terms of the sharp peak demands, was observed between winter and summer.

The broad peak has a peak demand of 70W/m^2 and had an initial rise in power demand occurring from 04:00, reaches peak demand at 12:30, and returns to the baseload value at 18:30.

5.4.4 School 40; Electric Heating (Figure 99)

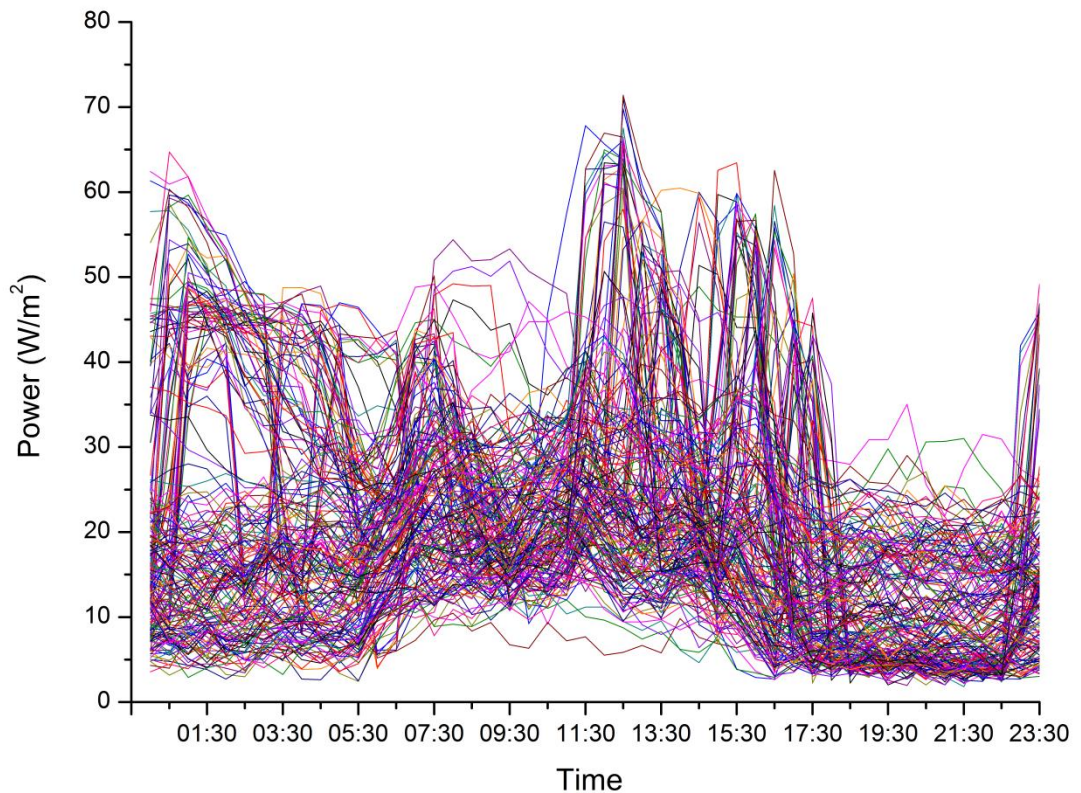


Figure 99 - Power Demand Profiles for School 40

The power demand profiles for school 40 were considered to be non-‘typical’ and hence were removed from the database. School 40’s power demand profiles have both a broad peak, and multiple sharp peaks occurring throughout the 24 hour period. The baseload of the broad peak varies from 5-20W/m² and has a peak demand of 35W/m² occurring at 10:30. The broad peak appears to rise from baseload at 05:30, and reaches a peak demand, before returning to baseload by 17:30. In contrast, the peak demand of the sharp peaks ranges from 40-75W/m², with the largest peak occurring at 12:30. The repetitive sharp demand indicated electric heating. The time period outside the school hours (when the school is shut) has a high baseload but is lacking any sharp peaks until 22:30. It can be assumed that this late evening peak is the heating/storage system being switched on in preparation of the following day.

5.4.5 School 41 Electric Heating (Figure 100)

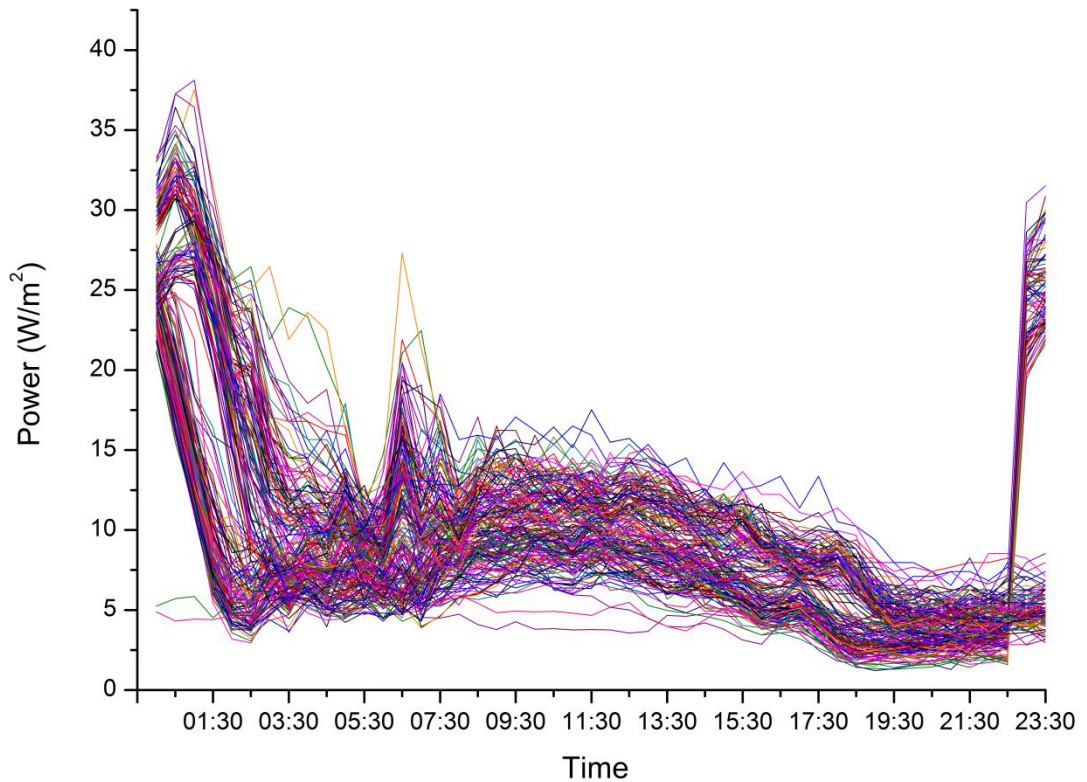


Figure 100 - Power Demand Profiles for School 41

The power demand profiles for school 41 exhibit both a broad peak demand and a sharp peak(s). The broad peak demand has a baseload of 4.7W/m^2 and a peak demand of 15W/m^2 . The demand rises from baseload at 02:30 and reaches a peak demand at 11:30. The subsequent return to baseload occurs at 18:30. In contrast the sharp peak demand occurs from 22:30 to 02:30 (duration of 4 hours), and has a peak demand ranging from 22-37 W/m^2 . This peak demand varied when the school data underwent seasonal analysis, with spring, summer, autumn and winter having peak demands (in terms of the sharp peak) of 33W/m^2 , 25W/m^2 , 28W/m^2 and $35\text{-}37\text{W/m}^2$ respectively.

5.4.6 School 43; Electric Heating (Figure 101)

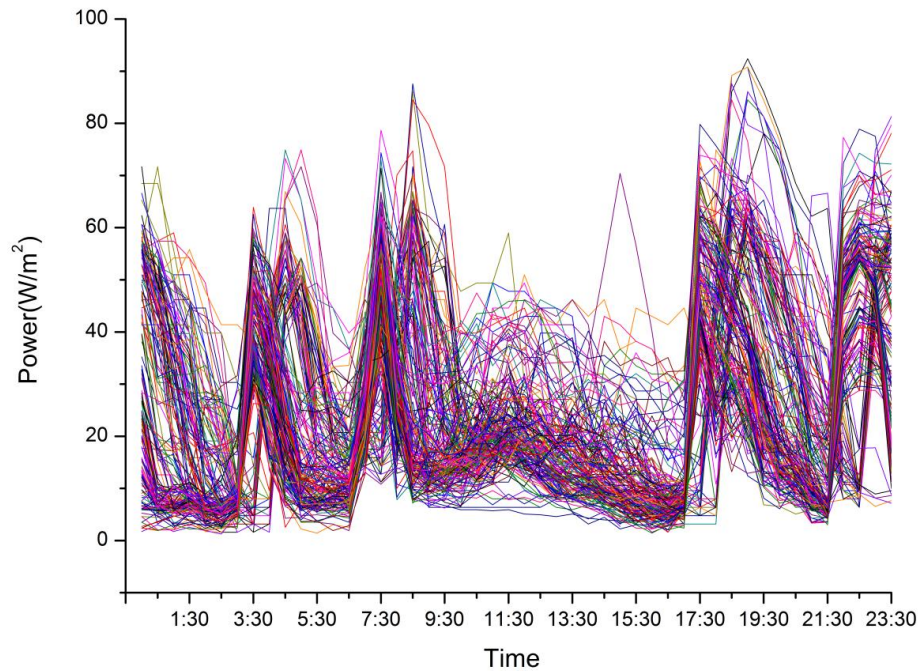


Figure 101 - Power Demand Profiles for School 43

Lastly, Figure 101 demonstrates the daily power demand profiles for school 43. The profiles include a small broad peak demand and five sharp peak demands. The sharp peaks have demands ranging from 60-90W/m², and occur at 00:00, 03:30, 07:30, 18:30 and 21:00. The broad peak occurs from 09:30, reaches a peak demand ranging from 22-60W/m² occurring at 11:30. The demand returns to the baseload value from 16:00 to 17:00.

The peak demands of the sharp peaks have duration of approximately two hours. It was discovered that these sharp peaks were associated with a small school that used electric storage heaters, opposed to gas boilers. The storage heaters are turned on during the night, and then the heat is released throughout the day.

5.5 High School Analysis

The high schools power demand profiles were separated from the other categories due to the observed difference between each type of schools. This category represented approximately 65% of the total collected database. In addition, the impact of construction age was also assessed. The high school dataset was sub-divided into two categories, schools constructed before 2000, and schools constructed after 2000. This subdivision was based on the clear divide between the age of schools (and in terms of number of schools built between 2005-2009).

The normalised power demand profiles for high schools is shown in Figure 102.

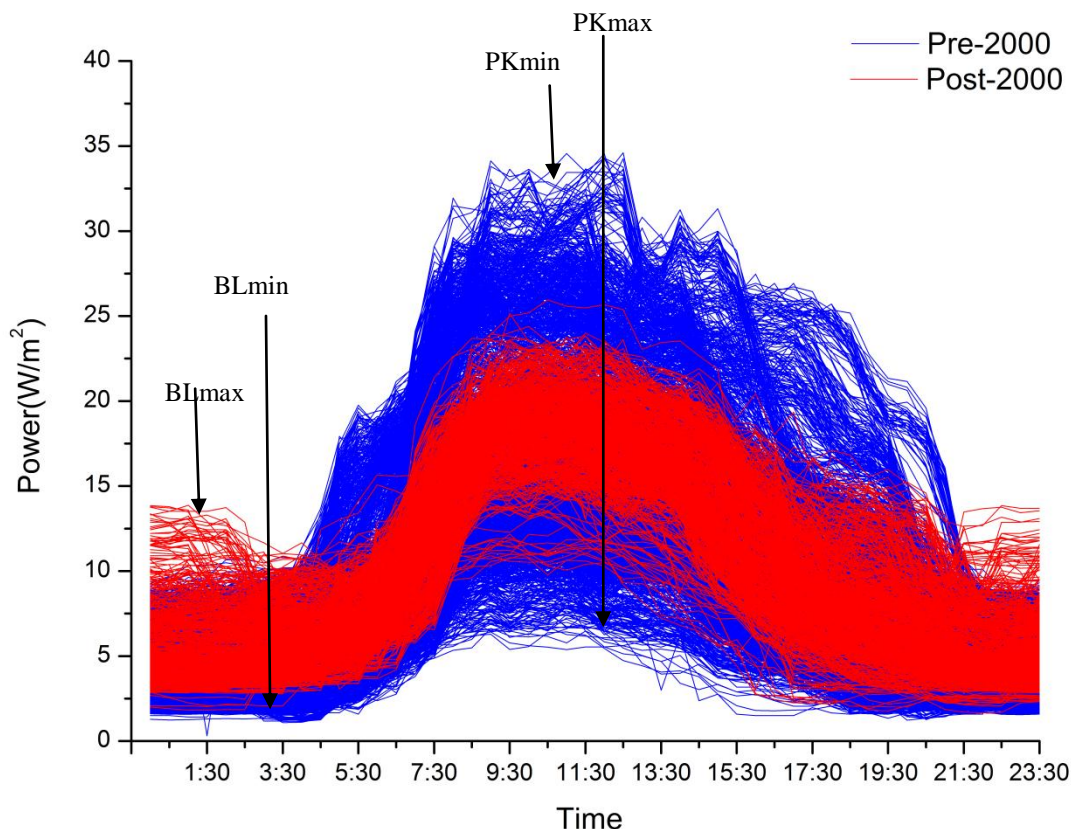


Figure 102 - High School Power Profiles

The removal of the school with electric heating had a clear and pronounced impact on the subsequent normalised power demand profiles. In addition, an analysis of the impact of high schools construction age was also undertaken.

Confining the datasets to schools with gas (or fossil fuel) heating resulted a normalised power demand profile consisting of a relatively broad peak ranging from 5-35W/m², and a baseload ranging from 2-14W/m².

Two distinct profiles were apparent if the age factor of the schools were included within the analysis. For high schools built post 2000, the subsequent power demand profiles were relatively congregated, with a baseload minimum (BLmin) and maximum (BLmax) of 2-13W/m² and a peak minimum (PKmin) and maximum (PKmax) of 5-25W/m². In contrast the schools built pre-2000 a greater variability in normalised power demand was observed. This variability is apparent if the corresponding minimum/maximum baseloads and peak demands are measured. The baseload minimum/maximum was 1-22W/m² and for the peak demand 5-35W/m².

The construction age of a school has a major impact on the subsequent power demand profiles obtained for schools. Schools constructed post-2000 had less variability in the power demand profiles. It was also important to determine if seasonal variations impacted on the normalised power demand profiles. In order to determine the

impact of seasons, its effect was examined on both the normalised power demand profiles for schools constructed post-2000 and pre-2000.

5.5.1 Seasonal Variation

The effect of seasonal variation on the normalised power demand profiles of high schools constructed post-2000 is shown in Figure 103.

It might be assumed that the seasons would have a marked influence on the subsequent power demand profiles for the schools. Power demand would be greater in winter, and less in summer. However, this assumption would appear not to be valid (Figure 103).

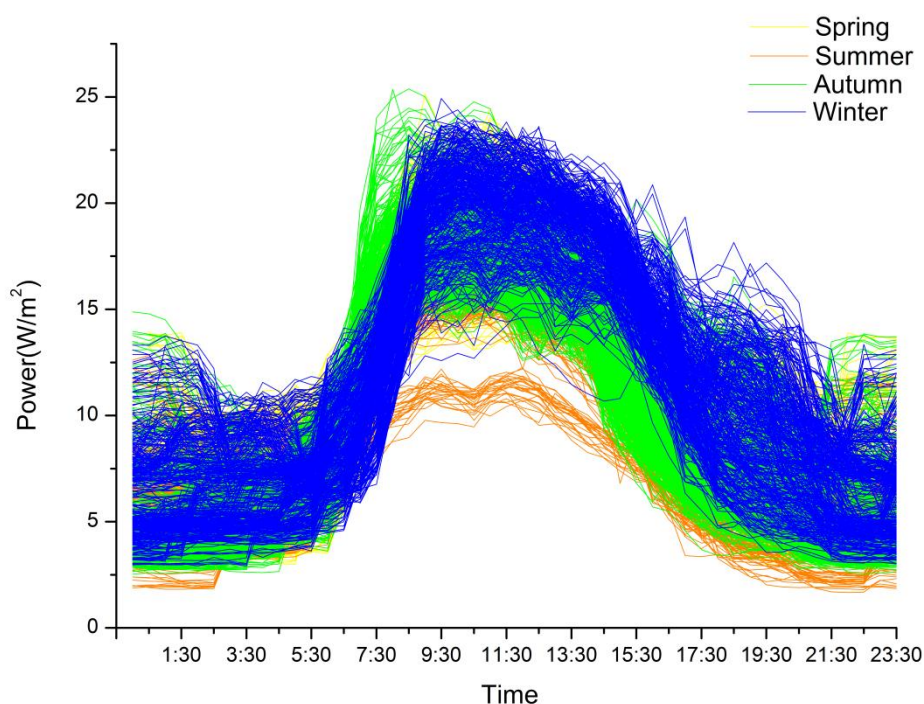


Figure 103 - Seasonal Variation on Post-2000 High Schools

The data set was separated into different seasonal profiles using the FORTRAN based organising program, as described in Chapter 3. The spring, summer, autumn and winter are represented by yellow, red, green and blue profiles. It is apparent that there is marginal seasonal impact on the peak and baseload demands. The overall shape of the power demand profile remains relatively constant. The main difference is slight overhang observed in the autumn profiles between 07:00 and 09:30, and a lower peak demand in summer from 07:30 to 15:30. This finding would be consistent with lower power demand in summer and a higher demand in winter. The lack of impact of the seasons on the normalised power demand is reinforced in Table 10.

Table 10 - Key Values from Season Comparison for Post-2000 High Schools

	<i>Baseload(min)</i>	<i>Baseload(max)</i>	<i>Peak(min)</i>	<i>Peak(max)</i>
	(W/m ²)	(W/m ²)	(W/m ²)	(W/m ²)
Spring	3	9	13	24
Summer	2	7	15	22
Autumn	2.5	10	15	23
Winter	3	10	16	23

There is only minimal variation in the region of 1-2W/m² in each value across baseload (minimum and maximum) and peak demand (minimum and maximum).

The analysis was repeated using the pre-2000 school data set.

5.6 Pre-2000 High Schools analysis

The separated normalised power demand profiles for schools constructed pre-2000 is shown in Figure 104. A sub-analysis was undertaken on this dataset to confirm the homogeneity of the data making up this dataset.

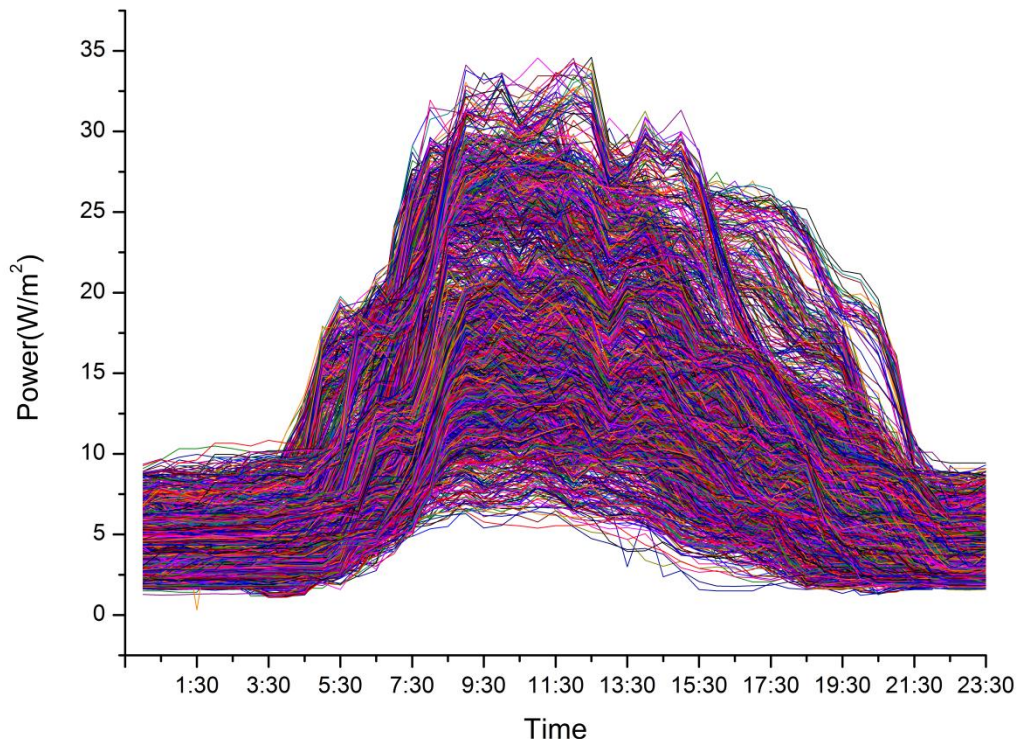


Figure 104 - Pre-2000 Schools Power demand profiles

The pre-2000 high school power demand profiles (Figure 104) exhibit a broad peak demand shape. The baseload varies from 3-9W/m² and the peak demand 5-35W/m². The demand remains at baseload until 04:00-04:30, when the demand increases to a peak demand by 12:30. The power demand then decreases to the

baseload value from 19:30 to 21:30. The time at which the power demand returns to baseload (from the peak demand) will vary depending on if the school has after school power demand. After school power demand is clearly visible, occurring from 04:00 to 21:30, with a peak demand of approximately $25\text{W}/\text{m}^2$.

The level of variation between the peaks and baseloads is a reflection of the wide range of pre-2000 schools, in terms of construction age and possible equipment differences, in contrast to the post-2000 high schools. Older schools may not have the same level of small power use in comparison to a larger purpose built school.

To gain a further insight into how power is used in the pre-2000 high schools, the seasonal influence was investigated.

The seasonal impact on the normalised power demand profiles for the pre-2000 high schools is shown in Figure 105.

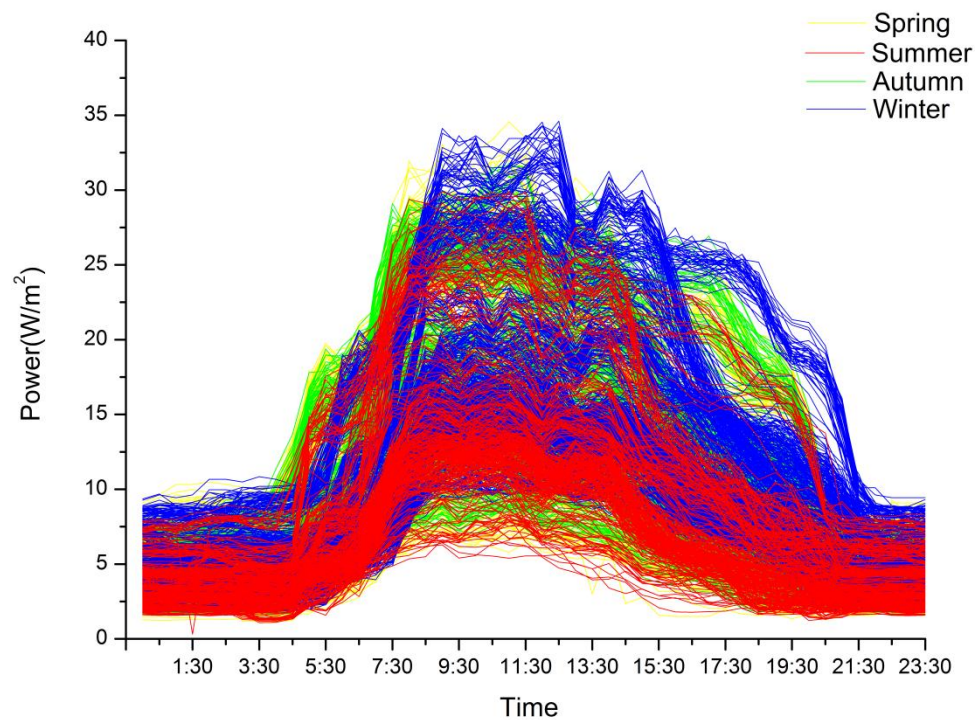


Figure 105 - Seasonal Pre-2000 Weekday Power Profiles

Spring, summer, autumn and winter are represented by the yellow, red, green and blue profiles respectively. Unlike the seasonal profiles for the post-2000 high schools, (Figure 103), it was evident that the seasons had a greater impact on the normalised power demand profiles of the schools constructed pre-2000.

The greatest difference in power demand appeared to be between the summer and winter profiles. In summer the baseload demand was in the range of $2\text{--}8\text{W}/\text{m}^2$ and peak demand in the range of $6\text{--}31\text{W}/\text{m}^2$. This changed in winter to $2\text{--}9\text{W}/\text{m}^2$ for the baseload and $10\text{--}35\text{W}/\text{m}^2$ for the peak demand. The seasons had less of an impact on

the duration of the broad peak. In spring, summer and autumn, the broad peak duration (time from rise to fall from/to baseload) was 16 hours respectively. In contrast this was increased to 17 hours in winter. The impact of the seasons on the normalised power demand is emphasised in Table 11. Minimal impact is observed in baseload (minimum or maximum) with a difference of 5W/m² in minimum peak demand and 5W/m² between maximum peak demand.

Overall, although the seasons have a greater impact on normalised power demand in buildings constructed pre-2000 than in schools constructed post-2000, the effect of the seasons does not appear to have a major impact on the demand.

Table 11 - Key Values from Pre-2000 High School Seasonal Comparison

	<i>Baseload(min)</i> (W/m ²)	<i>Baseload(max)</i> (W/m ²)	<i>Peak(min)</i> (W/m ²)	<i>Peak(max)</i> (W/m ²)
Spring	2	9	5	34
Summer	2	8	5	30
Autumn	2	8	9	31
Winter	2	9	10	35

Although the seasons appear to have minimal impact on the normalised power demand profiles in high schools, it would appear that in order to define a ‘generic’ power demand profile for this type of school, allowances will have to be made for the construction age of the schools in this category.

A similar analysis was undertaken on the normalised power demand profiles for primary schools within the collected database.

5.7 Primary Schools

The normalised power demand profiles over a 24 hour time period for the individual primary schools is shown in Figure 106.

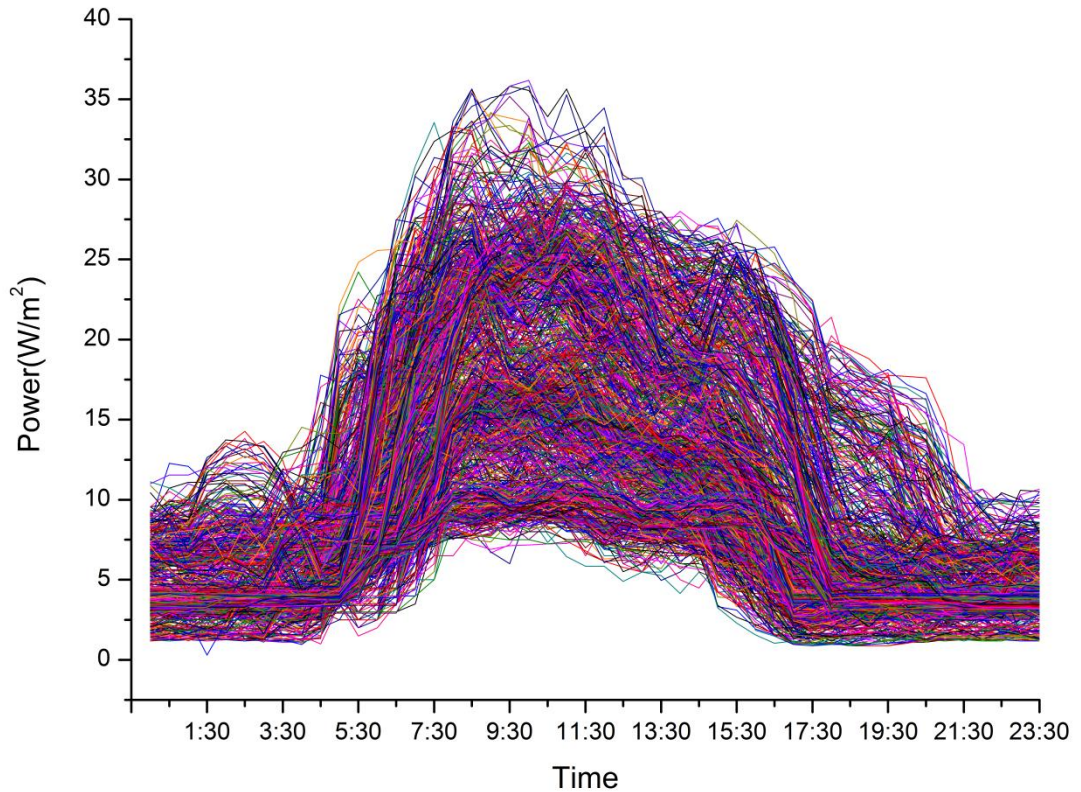


Figure 106 - Primary School Power Demand Profiles

The data from the primary school dataset, demonstrated a broad peak in power demand starting from 04:30, reaching a peak demand of 35W/m² at 10:00, and then falling gradually to baseload between 21:30 and 22:30. The minimum peak demand is in the region of 5W/m².

An analysis of the impact that seasons had on the normalised power demand in primary schools was undertaken.

5.7.1 Primary Seasonal Impact

The effect of seasons on the normalised power demand data for primary schools is shown in Figure 107.

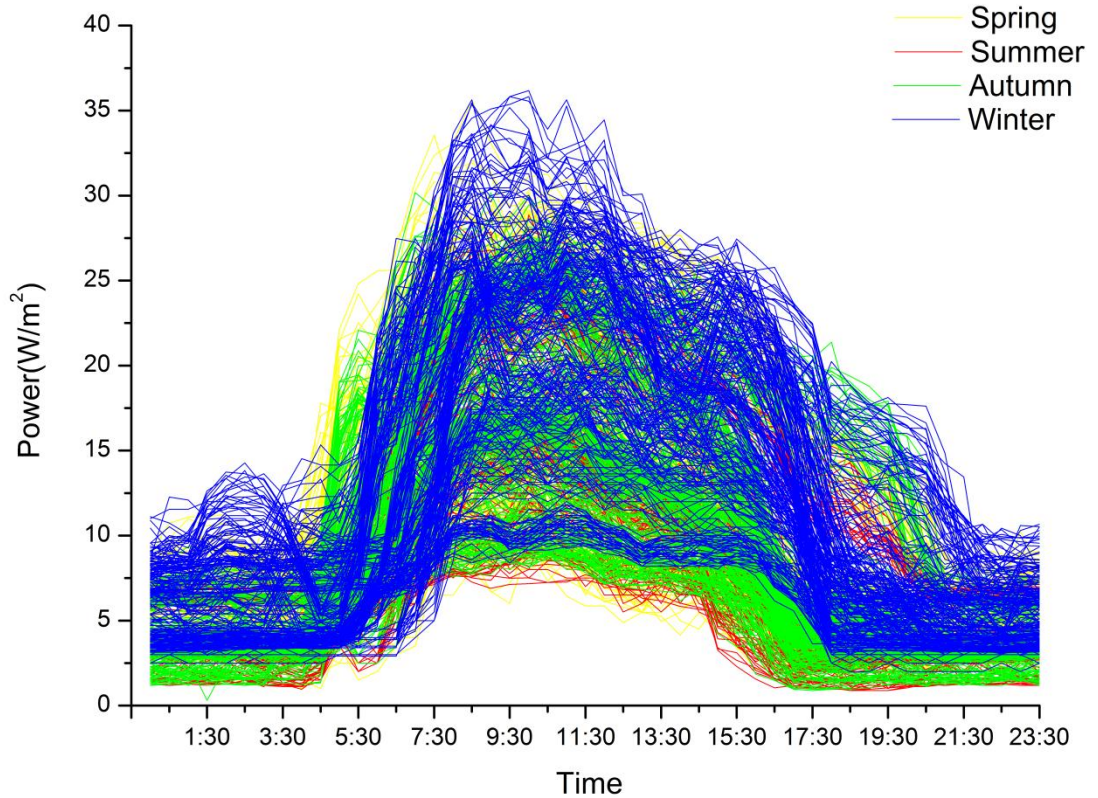


Figure 107 - Primary School Seasonal Comparison

Spring, summer, autumn and winter are represented by yellow, red, green and blue profiles. Marked variations in normalised power demand profiles were apparent in response to the seasons. Overall, baseload values range from 1-10W/m² between summer and winter respectively, and for peak demand, the range was from 9-35W/m² between summer and winter. The impact of the seasons on the baseload (minimum and maximum) and peak demand (minimum and maximum) for each season is shown in Table 12.

Table 12 - Key Primary School Seasonal Values

	<i>Baseload(min)</i> (W/m ²)	<i>Baseload(max)</i> (W/m ²)	<i>Peak(min)</i> (W/m ²)	<i>Peak(max)</i> (W/m ²)
Spring	1	9	6	32
Summer	2	7	6	28
Autumn	2	7	8	30
Winter	3	10	8	35

The difference in baseload for minimum was 2W/m², and 3W/m² for maximum. Similarly, the seasons had minimal impact on minimum peak demand, with a difference of 2W/m² between summer and winter, whereas a more pronounced difference between

summer and winter was observed in maximum peak demand, with a difference of 7W/m^2 .

This observation confirms the conclusion drawn from the analysis, for example as winter has the largest power demand, and summer having the smallest power demand. Additionally, it demonstrates that the spring and autumn power demands are similar in terms of baseload, and peak demand.

The last category of schools to be analysed was the specialised high schools.

5.8 Specialised Schools

The remaining schools in the dataset were the specialised high schools (4 schools). These schools are to educate high school aged children, and offer a closer teaching environment. The schools have lower pupil numbers than mainstream high schools, and include other power demand for specialised requirements, such as sensory rooms. Therefore, due to the potential differences in power demand, it was decided to analyse these schools separately from the high schools.

The normalised power demand profiles for the specialised high schools are shown in Figure 108.

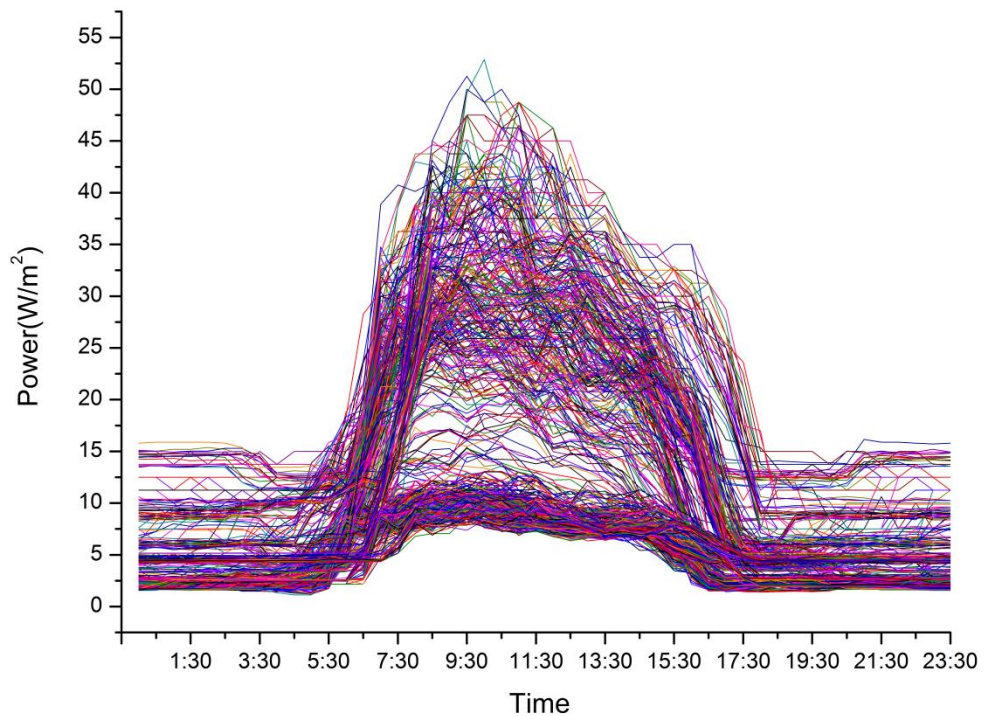


Figure 108 - Specialised School Weekday Profiles

The overall normalised power demand profiles for the specialised high schools appears to have more in common with the primary school (Figure 106) than high schools (Figure 102). The baseload data varied from $1\text{--}15\text{W/m}^2$ remaining fairly

constant from 00:00 to 05:00. The broad peak extended from 05:30 to 17:30 with a return to the respective baseload value. A demand of 50W/m² occurred at 10:30. Unlike high schools, where after school power demand is clearly visible (Figure 102), it is absent in the normalised demand profiles for the specialised high schools.

An analysis was undertaken on the effect of the seasons on the normalised power demand profiles over a 24 hour period for the specialised schools.

5.8.1 Specialised Seasonal Impact

The impact of seasons on the normalised power demand profiles from the specialised high schools is shown in Figure 109.

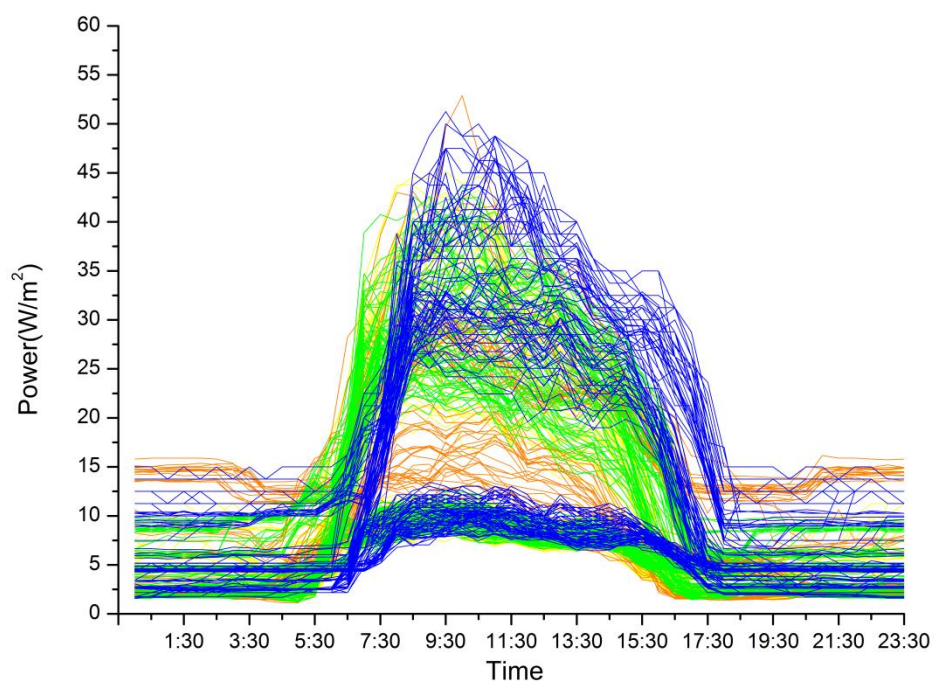


Figure 109 - Specialised School Seasonal Demand Comparison

Spring, summer, autumn and winter are represented by yellow, red, green and blue profiles. The seasons appeared a slightly different impact on power demand in specialised high schools than either primary schools or high schools. Whereas there were clear differences between summer and winter for both high and primary schools, in specialised high schools the difference appears to be between autumn and summer/winter for baseload, and summer/autumn and winter for peak demand.

Variations in normalised power demand profiles were apparent in response to the seasons. Overall, baseload values range from 1-15W/m² between summer and winter respectively, and for peak demand, the range was from 9-35W/m² between summer and winter. The impact of the seasons on the baseload (minimum and

maximum) and peak demand (minimum and maximum) for each season is shown in Table 13.

Table 13 - Key Specialised School Seasonal Values

	<i>Baseload(min)</i> (W/m ²)	<i>Baseload(max)</i> (W/m ²)	<i>Peak(min)</i> (W/m ²)	<i>Peak(max)</i> (W/m ²)
Spring	2	11	7.5	45
Summer	2	15	10	42
Autumn	2	10	7.5	42
Winter	2	15	7.5	50

The seasons had no impact on the minimum baseload but had a 5W/m² difference on the maximum baseload between autumn and summer/winter. Interestingly, autumn, winter and spring, had a lower minimum peak demand than summer; the difference being 2.5W/m². Although summer had the greatest demand at minimum peak, winter had the highest maximum peak demand; with a difference of 8W/m² between summer/autumn and winter.

An overall analysis of the effect of seasons and categories of the schools on both the baseload (minimum and maximum) and peak (minimum and maximum) demand was carried out.

5.9 Comparison of Results

The outcome of the seasonal analysis on the different school category datasets is shown in Table 14.

Table 14 - Comparison of Key Analysis results for each category of school

	Season	Baseload (min) (W/m²)	Baseload (max) (W/m²)	Peak (min) (W/m²)	Peak (max) (W/m²)
Post-200 High Schools	Spring	3	14	13	24
	Summer	2	13	15	22
	Autumn	2.5	15	15	23
	Winter	3	14	16	23
Pre-2000 High Schools	Spring	2	9	5	34
	Summer	2	8	5	30
	Autumn	2	8	9	31
	Winter	2	9	10	35
Primary Schools	Spring	1	9	6	32
	Summer	2	7	6	28
	Autumn	2	7	8	30
Specialised Schools	Winter	3	10	8	35
	Spring	2	11	7.5	45
	Summer	2	15	10	42
	Autumn	2	10	7.5	42
	Winter	2	15	7.5	50

Table 14 makes it possible to compare across the different school categories, and makes it possible to identify which seasons have a minimum or maximum impact on baseload and peak power demand. Overall the seasons have minimal effect on the baseload (minimum) demand in all school categories. However a greater variation is apparent in baseload maximum. This varied from 7W/m² in summer in and autumn in primary schools to 15W/m² in autumn in high schools constructed post-2000, and in specialised high schools in summer and winter.

A greater variation was apparent with minimum peak demand. This ranged from 5W/m² in spring and summer for high schools constructed pre-2000, to 15W/m² for summer and autumn for high schools built post-2000. Finally, the greatest variation

was observed with maximum peak demand. This varied from 22W/m² for summer for high schools built post-2000, to 50W/m² for specialised high schools in winter.

The ultimate aim of normalising power demand profiles is to develop a ‘generic’ or ‘typical’ demand profile for the different categories of schools in order to; a) create an energy reference tool, and b) to then create new energy performance benchmarks. The next section discusses the generation of these ‘generic’ or ‘typical’ profiles.

5.10 ‘Generic’ Profiles

Typical power demand profiles, or ‘generic’ profiles, are defined as the expected power demand for a building. This could be the average power demand obtained from a historical database or an ongoing analysis for an actual building. If average profiles are used they may mask key individual attributes within a power demand profile. The significance of this will be dependent on the relative contribution that the covered/hidden profile has in relation to the average profiles. Thus key data can be overlooked with average profiles.

An alternative to averaging the data was to apply a percentile analysis to the demand data. This creates several profiles, depending on the number of percentiles chosen. A key benefit of this approach is that energy efficiencies can be applied to the data. Ideally, a system would be created that allows a user to enter key building information, such as type, size, age and location. The simulation model would then create a series of power demand profiles that would represent the corresponding building. The output could then be mapped to the three benchmark categories; good, bad, and typical.

Lastly the profiles can be used to create new benchmarks for each school category. The benchmarks could be expressed as peak demand, baseload, daily consumption, weekly consumption, monthly consumption, seasonal consumption and annual consumption. This would in turn create a detailed benchmark table.

The generic profiles for each school category were generated. The data was analysed and five percentiles created; 10th, 25th, 50th, 75th and 90th. These percentiles were organised as follows; 10th ‘Excellent’, 25th as ‘Good’, 50th as ‘Typical’ and 75th as ‘Bad’ and 90th as ‘Very Bad’. The percentile analysis was undertaken on high schools (both pre-2000 and post-2000), primary schools and specialised high schools. The outcome from each school type will be discussed in turn. However, as the seasons had minimal impact on power demand of high schools built post 2000, seasonal variation was excluded from the generic profile for this category of school. In contrast the

seasonal effects on the generic profile from pre-2000 high schools, primary schools and specialised high schools were examined.

5.10.1 Post-2000 High Schools

The generic profile for power demand for high schools built post 2000 is shown in Figure 110.

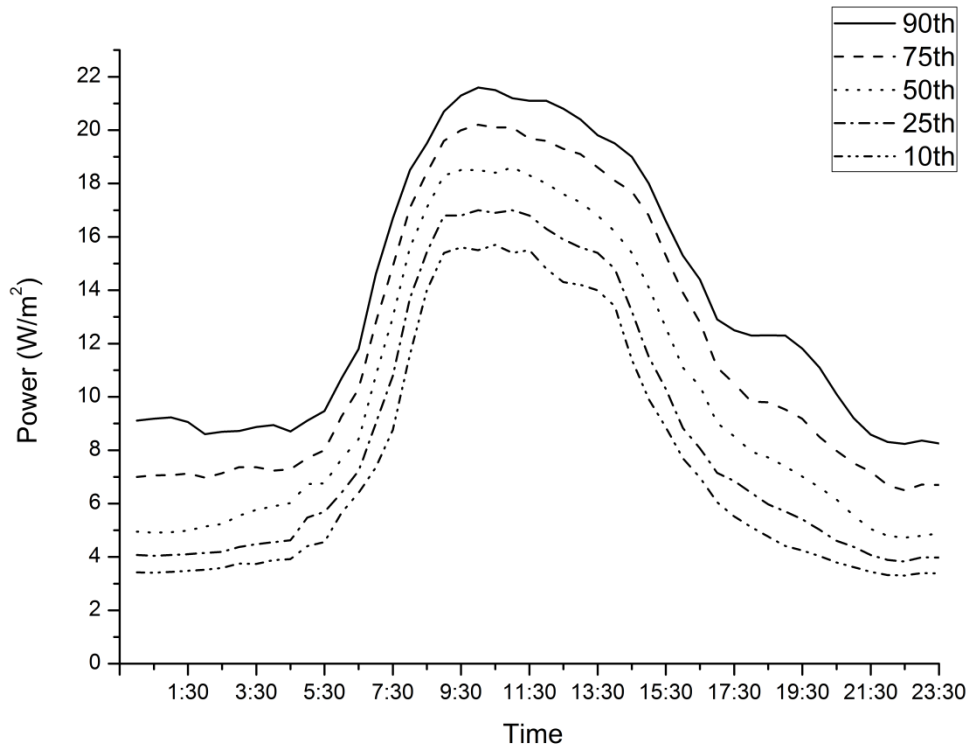


Figure 110 - Post-2000 High school Generic Profiles

Five unique power demand profiles representing the post-2000 high schools were established in Figure 110. Each profile has a varying baseload and peak demand. The baseload for the 10th, 25th, 50th, 75th and 90th were 3W/m², 4W/m², 5W/m², 7W/m² and 9 W/m² respectively. The peak demands for the Post-2000 high schools were 15.5W/m², 17W/m², 18.5W/m², 20.2W/m² and 21.5W/m² for each percentile (in ascending order) (Table 15). The findings in Table 15 are consistent with the view that the more efficient a school is, the lower its baseload and peak demand.

Table 15 - Post-2000 Generic Outputs

Percentile	Baseload (W/m ²)	Peak(W/m ²)	Daily Energy consumption (Wh/m ²)
10 th	3	15.5	182.96
20 th	4	17.0	209.42
50 th	5	18.5	244.88
75 th	7	20.2	289.36
90 th	9	21.5	329.02

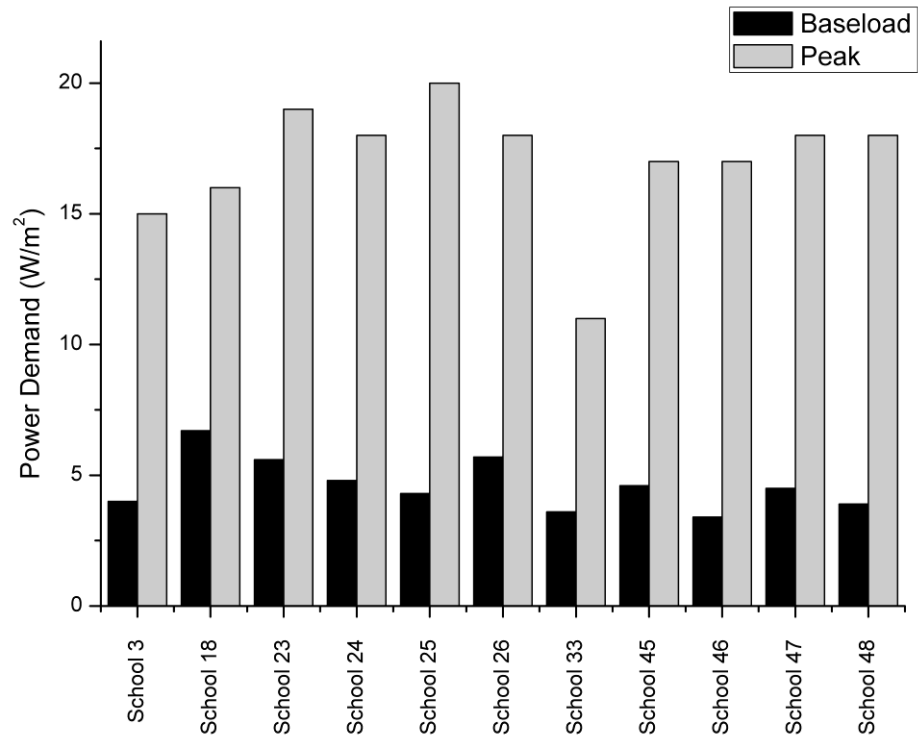


Figure 111 - Comparison of Baseload and Peak demand for each Post-2000 High School

To determine if this finding (low baseload results in a low peak demand) was applicable across the entire post-2000 high school dataset, the average baseload values and average peak demands were determined and compared (Figure 111). The results show that the school with the largest baseload (school 18, with a value of 6.7W/m²) does not have the largest peak power demand (school 25 has the largest peak demand, with a value of 20W/m²). Interestingly, the school with the lowest baseload (school 33, with a value of 3.6W/m²) has the smallest peak demand (11W/m²).

The average generic daily energy demand can also be investigated. Table 15 demonstrates the key outputs of the generic post-2000 high school power demand profiles. The energy consumption increased as the percentile increased. This was to be expected, due the increasing peak demands of the percentiles. The main advantage of including the ‘typical’ daily energy consumption of each percentile is that it can be used in accordance with the power demand profiles. This in turn can be used as a

benchmarking system that can allow users to determine what schools potential power demand could be and in turn the possible energy requirement.

A similar analysis was undertaken in high schools constructed pre-2000. As mentioned previously, the impact of seasons on the generic profile was also examined.

5.10.2 Pre-2000 High Schools

The influence of the seasons on the generic profile derived for high schools built pre-2000 is shown in Figure 112.

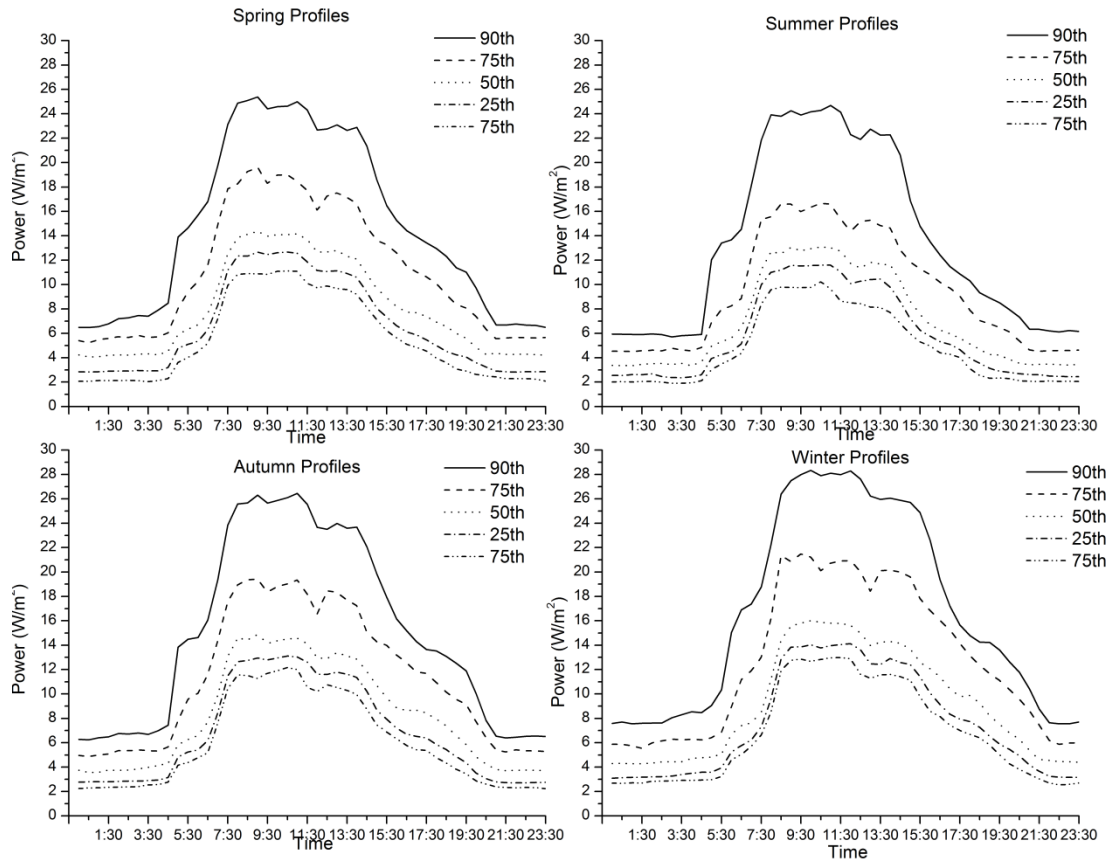


Figure 112 - Pre-2000 Generic Profiles

The figure demonstrates five percentile profiles for each season, resulting in twenty different profiles. Baseload, peak demand and daily energy consumption were used as indicators to evaluate the impact that the seasons had on the respective generic profiles.

The general power demand profiles appeared to be fairly similar, with marginal differences across the seasons or percentiles. Slight variation occurs in the post-2000 after school power demand, with the characteristic after school demand profile evident in the spring, autumn and winter, but not in summer. This was more noticeable at the 90th percentile.

The effect of the seasons on these indicators of power use is shown in Table 16.

Table 16 - Pre-2000 Generic Profile Outputs

<i>Percentile</i>	<i>Season</i>	<i>Baseload</i> (W/m ²)	<i>Peak</i> (W/m ²)	<i>Energy Consumption</i> (Wh/m ²)
10 th	Spring	2.0	10.5	119.5
	Summer	1.9	10.2	115.0
	Autumn	2.2	12.2	143.5
	Winter	2.5	13.0	162.6
25 th	Spring	2.7	12.3	153.6
	Summer	2.4	11.6	139.7
	Autumn	2.7	13.1	164.1
	Winter	3.1	14.1	183.4
50 th	Spring	3.8	14	190.8
	Summer	3.3	13.1	167.4
	Autumn	3.6	14.9	197.4
	Winter	4.3	16.0	219.0
75 th	Spring	5.4	18.7	262.4
	Summer	4.5	16.7	226.3
	Autumn	4.9	19.4	270.9
	Winter	5.5	21.5	304.5
90 th	Spring	6.6	25.2	357.1
	Summer	5.7	24.7	323.6
	Autumn	6.2	26.4	360.8
	Winter	7.6	28.3	399.6

The analysis of the post-2000 high school data indicated that there was identifiable seasonal variation in these indicators. This variation was also evident within the percentile analysis profiles, see Figure 112. Within each percentile, the seasons had a small effect on baseload with a difference of 0.6W/m² at the 10th percentile to 1.9W/m² at the 90th percentile across the seasons. In contrast a different profile was observed in peak demand and daily energy consumption. The lowest difference in seasonal effect on peak was 2.5W/m² at the 25th percentile, and the largest difference in peak was 4.8W/m² at the 75th percentile. Energy consumption reflected peak demand, with the lowest seasonal impact at the 25th percentile (43.7W/m²) and the largest seasonal difference at the 75th percentile, with a value of 78.2W/m².

The percentile analysis was repeated on the primary school dataset.

5.10.3 Primary Schools

The primary schools were analysed using the same process that was applied to the pre-2000 high schools and the generic outputs shown in Figure 113.

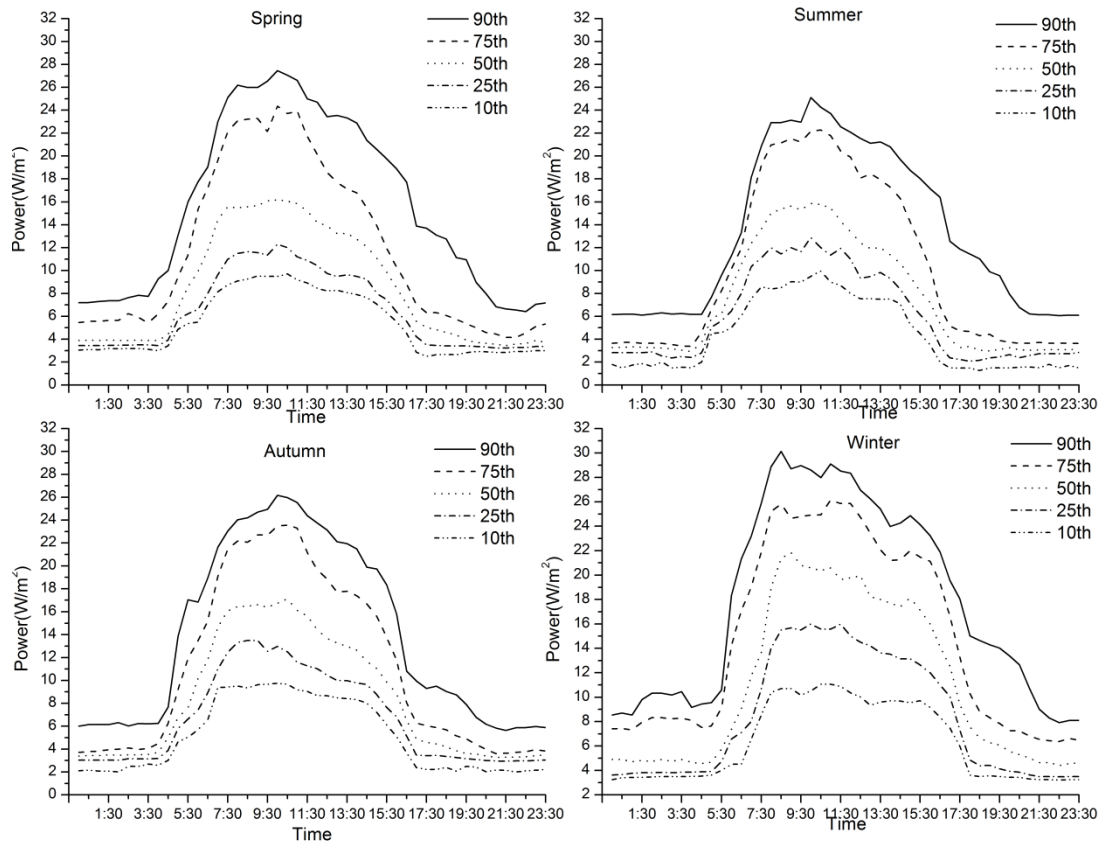


Figure 113 - Primary School Seasonal Generic Profiles

On initial inspection there is a general rise in peak demand in the cooler months (autumn and winter), than the warmer months (spring and summer). This was consistent with the seasonal analysis of the average power demand profiles. In the 90th percentile, a profile was observed that was similar to the after school power demand, as found in high schools. This is of interest, as this demand profile was not evident in the normalised power demand profiles for primary schools Figure 102. The power demand indicators of baseload, peak and daily energy consumption data for each percentile are presented in Table 17.

Table 17 - Primary School Generic Key Details

Percentile	Season	Baseload	Peak	Energy Consumption
		(W/m ²)	(W/m ²)	(Wh/m ²)
10 th	Spring	2.50	9.70	128.64
	Summer	1.26	9.94	103.56
	Autumn	2.00	9.75	121.95
	Winter	3.21	11.06	150.56
25 th	Spring	3.24	12.30	153.97
	Summer	2.07	12.89	141.39
	Autumn	2.94	13.50	159.20
	Winter	3.48	16.00	199.82
50 th	Spring	3.43	16.17	202.91
	Summer	2.92	15.87	179.41
	Autumn	3.28	17.11	201.31
	Winter	4.41	21.85	263.92
75 th	Spring	4.16	24.36	282.22
	Summer	3.36	22.29	244.30
	Autumn	3.61	23.55	267.88
	Winter	6.36	26.14	355.86
90 th	Spring	6.40	27.48	376.50
	Summer	6.06	25.11	322.43
	Autumn	5.64	26.18	336.94
	Winter	7.91	30.12	429.14

The analysis of the primary school data indicated that there was identifiable seasonal variation in these indicators. This variation was also evident within the percentile profiles, see Figure 113. Within each percentile, the seasons had a small effect on baseload with a difference of 1.41W/m² at the 25th percentile to 3W/m² at the 75th percentile across the seasons. In contrast a different profile was observed in peak demand and daily energy consumption. The lowest difference in seasonal effect on peak was 1.36W/m² at the 10th percentile, and the largest difference in peak was 5.01W/m² at the 90th percentile. Energy consumption reflected peak demand, with the lowest seasonal impact at the 10th percentile (46.7W/m²) and the largest seasonal difference at the 75th percentile, with a value of 111.6W/m².

To determine if the daily energy consumption (per floor area), was linked to the baseload (or the peak) demand, the values from Table 17 were plotted and analysed using linear regression analysis. The results of this analysis are shown in Figure 114.

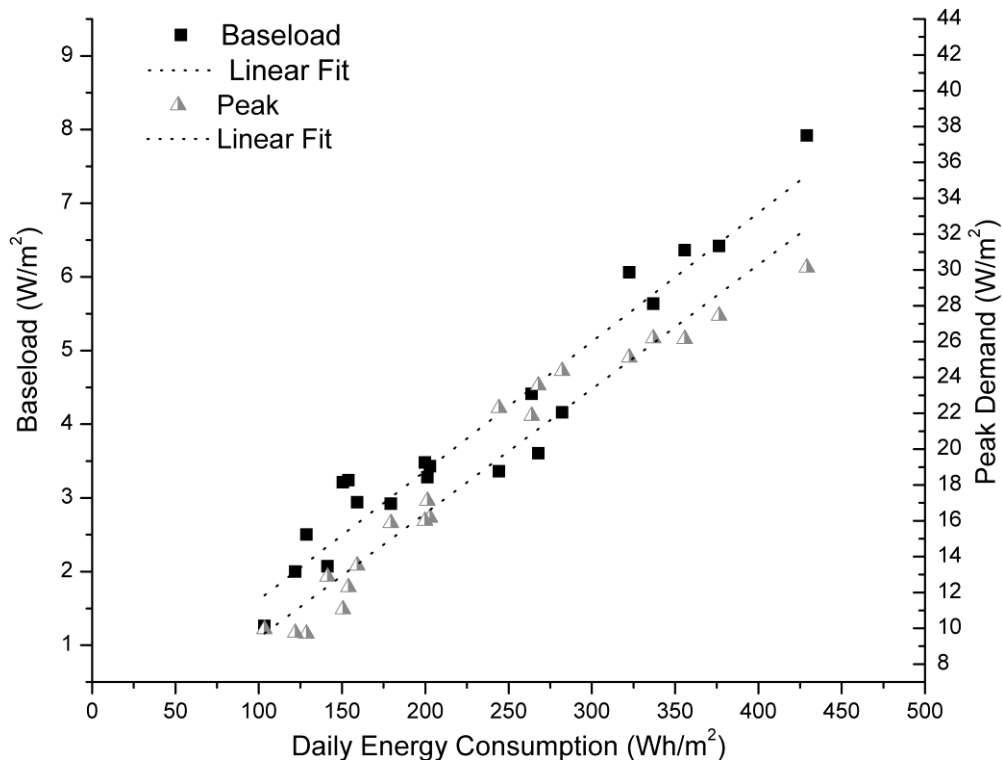


Figure 114 - Regression Analysis of baseload/peak demand against daily energy consumption

Linear regression analysis of the baseload (represented by squares) against daily energy consumption gave rise to a linear relationship with a residual coefficient (R^2) of 0.93, indicating a strong relationship between these variables. Similarly, linear regression analysis of peak demand (represented by triangles) against daily energy consumption gave rise to a linear relationship with a residual (R^2) of 0.95. Thus the results indicated that both the baseload and peak demand can influence the daily energy consumption. However, it appeared that the peak demand had a marginally stronger influence.

Finally, a percentile analysis of the specialised high school database was undertaken.

5.10.4 Specialised Schools

The specialised high schools were analysed using the same process that was applied to the pre-2000 and post-2000 high schools and primary schools, with the generic outputs shown in Figure 115.

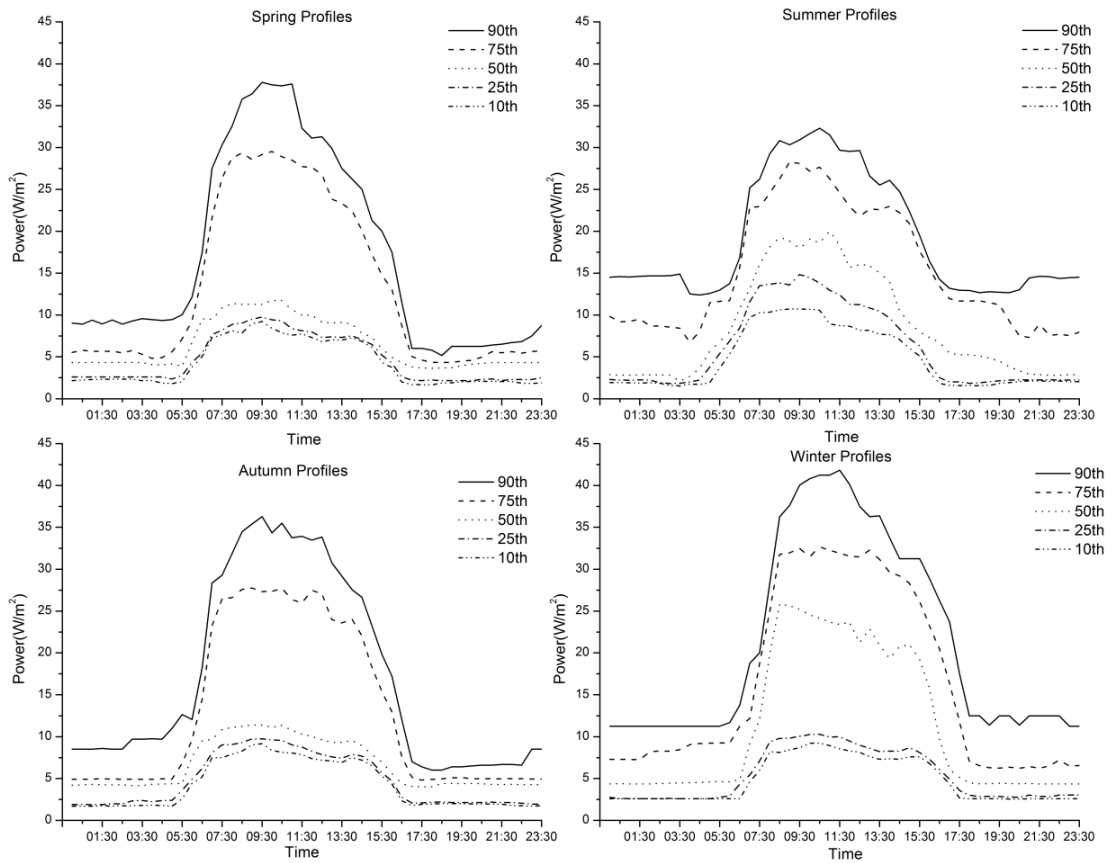


Figure 115 - Specialised School Generic Profiles

The visual analysis of the specialised schools concluded that the power demand of the specialised schools was influenced by the changing seasons. This difference was more pronounced between summer and winter with the profiles for spring and autumn looking broadly similar. The key indicator data of baseload, peak demand and daily energy consumption are summarised in Table 18.

Table 18 - Specialised School Generic Outputs

Percentile	Season	Baseload (W/m ²)	Peak (W/m ²)	Energy Consumption (Wh/m ²)
10 th	Spring	1.65	9.22	100.49
	Summer	1.54	10.73	113.80
	Autumn	1.66	9.16	100.57
	Winter	2.54	9.22	113.94
25 th	Spring	2.17	9.75	111.95
	Summer	1.82	14.84	146.13
	Autumn	1.87	9.76	113.01
	Winter	2.60	10.30	128.21
50 th	Spring	3.65	11.72	155.02
	Summer	2.14	20.04	205.94
	Autumn	3.99	11.39	159.36
	Winter	4.34	25.83	267.25
75 th	Spring	4.34	29.52	319.00
	Summer	6.69	28.28	366.11
	Autumn	4.82	27.76	311.88
	Winter	6.22	32.71	394.84
90 th	Spring	5.15	37.79	409.26
	Summer	12.38	32.29	459.65
	Autumn	6.00	36.29	412.80
	Winter	11.25	41.82	512.95

The analysis of the specialised high school data indicated that the seasons had an effect on the indicators at each percentile, see Table 18. The seasons within each percentile, had an effect on baseload with a difference of 0.78W/m² at the 25th percentile to 7.35W/m² at the 75th percentile across the seasons. A similar profile was observed in peak demand and daily energy consumption. The lowest difference in seasonal effect on peak was 1.57W/m² at the 10th percentile, and the largest difference in peak was 14.4W/m² at the 50th percentile. Energy consumption reflected peak demand, with the lowest seasonal impact at the 10th percentile (13.46Wh/m²) and the largest seasonal difference at the 50th percentile, with a value of 112.23Wh/m².

The spring and autumn have almost identical power demand, whereas the summer and winter have very different demands. In addition, although the summer

peak demands are generally the lowest (in comparison to the other seasons), summer generally has the second highest daily energy consumption.

The results from the percentile analysis emphasised the usefulness of a generic power demand profile, as a tool, for predicting energy demands in a particular school (or building in general). However, care must be taking in using these generic profiles, as seasonal factors will influence the choice of generic profile selected for defining a building’s power demand.

The previous sections have discussed the creation of generic profiles for the four different identified categories of school. Each category had unique seasonal generic profiles, with varying baseloads and peak power demand. To better understand how the profiles change between the different categories, the seasonal profiles for each type of school should be compared.

5.10.5 Comparison of Generic Profiles

A comparison of the generic power demand profiles, for each category of school derived from the 50th percentile is shown in Figure 116. The 50th percentile was chosen, as it relates to the ‘typical’ benchmark grouping, and represents the median power demand.

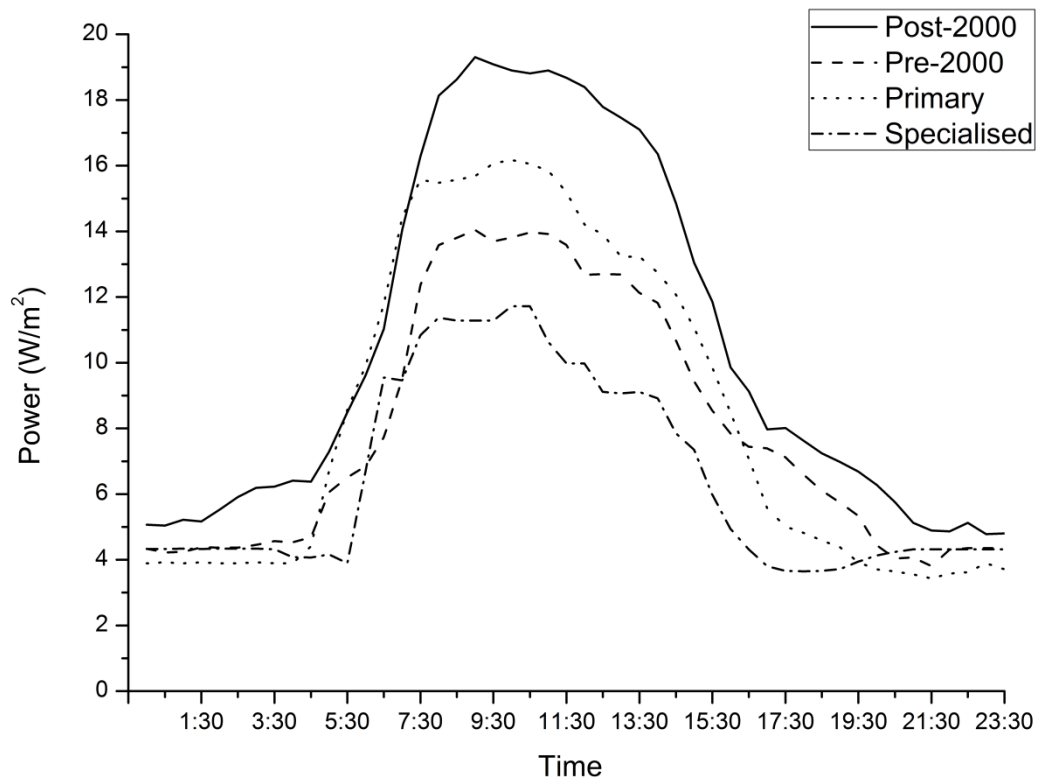


Figure 116 - Seasonal Generic Profile Comparison

A pronounced difference exists in the generic profiles, established for each of the school categories. With respect to peak power demand, the rank order is; post-2000 high schools, primary schools, pre-2000 high schools, specialised high schools (from high to low peak demand). The difference in peak power demand between the post-2000 high school (with the lowest peak demand) and the specialised high school (with the highest peak demand) was 13W/m². Although the four categories of schools had similar baseload values (ranging from 4-5W/m²), some differences in the rate of rise in demand and subsequent fall in demand were apparent. Specialised schools had the most rapid rise and fall in power demand, whereas the pre-2000 high schools showed the longest decay in power demand.

The comparison of generic profiles using the 50th percentile identified clear differences between the school types. This finding emphasises the importance of using the appropriate generic profile as a basis for predicting power demand in a particular type of school.

5.11 Generic Benchmarks

The creation of generic profiles for each of the school type, season and for each percentile provided an insight into the benefits of developing generic profiles. As well as the generic power demand profiles, key information such as the varying baseloads, peak demand and daily energy consumption was also determined. The daily energy consumption data for each school type, percentile and season was extrapolated to determine annual energy consumption figures that in turn can be compared with the published benchmarks, see section 2.6.2.2. The calculated generic seasonal benchmarks for the schools are found in Table 19.

Table 19 - Generic Seasonal Benchmarks

		Total Seasonal Energy Consumption (kWh/m ²)				
		10 th	25 th	50 th	75 th	90 th
Post2000	Sp	13.72	15.41	17.85	21.13	26.63
	Su	7.81	9.93	11.97	14.74	17.769
	Au	13.49	14.97	17.07	19.52	22.51
	Wi	13.78	15.50	18.05	21.09	24.22
Pre-2000	Sp	7.95	10.76	13.55	13.43	25.86
	Su	4.95	6.67	8.55	12.39	18.41
	Au	9.13	11.50	14.18	19.66	26.66
	Wi	10.05	12.01	14.57	20.66	27.65
Primary	Sp	9.07	10.89	14.08	19.80	27.66
	Su	4.46	6.71	8.67	11.46	18.16
	Au	8.42	11.28	14.30	19.20	25.15
	Wi	10.19	13.07	17.64	24.62	30.65
Specialised	Sp	6.80	7.77	11.62	21.42	27.55
	Su	5.17	6.49	11.04	17.02	33.19
	Au	6.93	7.84	11.67	21.82	29.27
	Wi	7.56	8.71	17.02	24.25	34.52

In order to compare the generic benchmarks with the published benchmarks (which are generally presented in annual opposed to seasonal consumption figures), the data was extrapolated to produce annual energy consumption benchmarks. The results from this scaling are found in Table 20.

Table 20 - Generic Annual Benchmarks

		Annual Energy Consumption (kWh/m ²)			
		Post	Pre-2000	Primary	Specialised
10 th		48.82	32.09	32.16	26.47
25 th		55.83	40.95	41.98	30.83
50 th		64.96	50.87	54.70	51.36
75 th		76.48	66.15	75.10	84.52
90 th		91.14	98.60	101.63	124.54

5.12 Generic Profile Conclusion

This chapter focused on analysing the half hourly power demand profiles for each school in the school electricity database. Key differences between this results chapter and the previous (initial) results chapter, is that all half hourly power demand data for each school is analysed, instead of annual consumption data or average power demand data. Additionally, only school power demand data is analysed opposed to office or thermal data as analysed in the previous chapter.

This chapter used the conclusions gained from the initial results chapter, and applied them to the analysis of the total school database. The chapter systematically accounted for weekend power demand differences and electrically heated schools, by demonstrating the impact on the total demand profiles after their removal. Additionally, factors like categorisation, age of construction and seasonal impact were also accounted for, and this chapter presented the demand profiles for each separated database. This chapter demonstrated that each category of school (and age category for the high schools) had different minimum and maximum peak and baseload demands, as well as varying seasonal impact.

This chapter then calculated the ‘generic’ power demand profiles for each of the separated school databases (pre-2000, post-2000 schools, primary, and specialised high), as well as associated energy performance benchmarks. The calculated ‘generic’ power demand profiles were also compared against each other to further highlight the differences in demand between each school type, as well as reinforce the requirement of school categorisation.

The initial results are analysed and discussed in the following chapter.

Chapter 6 DISCUSSION: INITIAL ANALYSIS

6.1 Initial Analysis

The initial analysis of the collected databases provided an insight into both the quality of the data, and how each of the collected schools consumed electrical energy. The initial analysis of the data was separated into several key sections. These sections included analysing the total annual electrical energy consumption against floor area and construction age, the electrical energy intensity against floor area, and comparing the annual electrical energy consumption against published benchmarks. Each of these initial analysis sections will be discussed in turn.

6.1.1 Energy Consumption Against Floor Area

The first stage of the electrical data analysis involved determining how the floor size impacted on the buildings total energy consumption. The total annual energy consumption of each school and the corresponding floor area was plotted, and linear regression analysis applied. The results indicated that there was a strong link between the two variables as indicated by the R^2 value being equal to 0.55. One unexplained outcome was that although the general trend (in floor area and energy consumption) was established, the smallest building did not have the smallest energy consumption, and neither did the largest building have the highest energy demand. The identified link between the floor area and energy consumption was accepted even though there were several schools (outliers) that did not conform to the trend. For a stronger link, hence an increase in R^2 value, the database could be expanded to cover a wider number and range of schools.

The analysis also introduced initial categorisation of schools, by highlighting the differences between the high schools (black squares) and the primary schools (white squares), see Figure 64. The results demonstrated that there were several high schools that had a lower energy consumption than the primary schools, contradicting the assumption that primary schools would have a lower annual electrical consumption than the larger high schools. However, the results do indicate that generally the primary schools have a lower consumption, with all primary schools (bar the larger primary school at 8835m²) having an annual energy consumption at or below the 500,000kWh/yr value. In comparison, the majority of the high schools were clustered between 400,000-1,000,000kWh/yr values.

Although the relationship between the total annual electrical energy consumption and floor area proved to be fairly strong, it suggested that there are further

normalisation variables required to fully understand how energy consumption varies between the different schools. One further normalisation variable investigated, although briefly, was the differences in energy consumption between categories of school. If the school database was to be expanded this categorisation would be essential in determining why there is variation in power demand between the schools within the database.

6.1.2 Energy Intensity Against Floor Area

The second stage of the initial analysis was investigating how the calculated energy intensity (in kWh/m²/yr) varied in building size (or total floor area). This assisted in highlighting how energy intensity varied across build size. The results, (see Figure 65), highlighted that there were several outliers, that had the highest energy intensity, and the smallest total floor area. The three outliers below 2000m² were identified as high schools and the outlier at ~2000m² was a primary schools. The majority of the other schools had annual energy intensity between 30-100kWh/m² and hence any school within this range can be considered to have ‘typical’ energy intensity. Subsequently, any outliers represent schools with abnormal energy intensity, such as the four identified outlying schools.

The three outlying high schools were identified as schools 7, 17 and 43, and the outlying primary school was identified as school 14. The high energy intensity (approximately double what was defined as ‘typical’ energy intensity) and small floor area (2000m² and under) suggested that the schools contained and utilised high energy consuming systems. Examples of possible high energy consuming systems could be air conditioning or electric heating. Further investigation revealed that the four identified outlying schools incorporated electric heating. The energy required for an electric heating system in addition to the schools normal energy consumption (lighting, IT) would result in a high energy intensity, when compared with other non-electrically heated schools.

The results also demonstrated that there were several high schools that had a lower energy intensity than the primary schools. It was expected, that the primary schools would have lower energy intensity than the high schools, due to primary school having less small power equipment. High schools can have large computer labs, as well as flood-lit sports facilities, and possibly a swimming pool whereas primary schools do not (and hence high schools should have a high intensity). The high schools that have intensities smaller than primary schools, could have the additional small power and

lighting, however also an improved energy efficiency. Increased energy efficiency (such as the measures discussed in 2.9) in the schools equipment would result in lower overall energy intensity.

Future analysis of the energy intensity against floor area of the schools in the could be extended to account for other factors including type of heating and year of construction. This could provide further detail into the differences (if any) in energy intensity between each school type and between each school within each category.

6.1.3 Energy Consumption against Construction Age

The second normalisation factor examined, was how the age of construction influenced the energy consumption of each school. The building materials, school design and allowed tolerances (within the construction stage) can vary (as improvements throughout the building's lifetime have occurred). The initial hypothesis was that newer schools, or those identified as being built after 2000, should have a lower energy consumption than the older school (those identified as being built before 2000). This was due to new schools having better construction standards and improved energy efficient measures. Figure 66 shows the results from plotting the total annual energy of each school against its corresponding construction age.

The results indicated that there was no significant relationship between the total annual energy consumption, and the year of construction. This lack of a relationship was further highlighted when linear regression analysis was applied, and the output residual (R^2) being equal to 0.02. The results demonstrated that the majority of newer schools, or those built after 2000, were closely clustered between 50-100kWh/m²/yr values. This suggested that the schools had a similar equipment list, had the same construction specifications, and possibly similar user behaviour. There were two outliers within the post-2000 schools, one at 141kWh/m²/yr and one at 213kWh/m². Further investigation revealed that these two schools, school 41 and 43, had electric heating (in the form of either storage or space). As discussed in Section 6.1.2, the increased demand from electric heating would result in a high energy consumption figure than that of a school that utilised fossil fuel heating.

The pre-2000 schools mainly clustered between 25-100kWh/m²/yr and had construction ages between 1940 and 1990. At this stage of the analysis it was evident that there were several older schools that had lower energy consumption than the newer schools. Unfortunately, the data was not separated into school categories, hence the identified lower energy consuming schools consisted of primary schools. The older

schools had four outliers at, 142kWh/m², 192kWh/m², 193kWh/m² and 212kWh/m². These schools were also identified as to having electric heating (either space or storage), and hence the cause of their high energy consumption.

One issue arose when analysing the total annual energy consumption against the corresponding floor area, relating to determining when the school was actually constructed. For the post-2000 schools, this information was readily available, however for the older schools, this data proved more difficult. Several of the pre-2000 schools have undergone major renovation/retrofitting resulting in an old school becoming more energy efficient and having equipment/systems similar to a newer school. Examples of schools that have under gone renovation were highlighted in Figure 66 (by the white squares). The school built in 1893, and that represents one of the renovated schools, has an electrical energy consumption similar to several of the schools between 1940-1990. Unfortunately, energy consumption data relating to the school before the renovation (taking place in the 1930's and 1960's) was not available, so the true impact of the retrofitting of the older schools was unknown.

The results indicated that there was a wide range of construction dates, and that there were newer schools that had a total energy consumption that far exceeded that of the older schools. Although there was not a significant link between construction age and total electrical energy consumption, broadly similar consumption was exhibited in the pre-2000 high schools, as well as the post-2000 high schools. The clustering of the newer schools suggested that the age of the school, at least in terms of pre-2000 and post-2000, was important to consider for any further analysis. Lastly, the results from analysing Figure 66 indicated that the total annual energy consumption of the schools did not have to be normalised by construction age, removing this as a normalisation variable. However, although an identifiable link between construction age and energy consumption could not be established, a clear divide between the pre-2000 and post-2000 schools existed.

6.1.4 Benchmarking the Collected Database

The next stage in the initial analysis was to benchmark the collected database and compare the outcomes to the published benchmarks, as found in Table 2 and Table 3 (section 2.6). The data was separated into the three different categories of school; high, primary and specialised high, as it was evident from the previous analysis stages that building/school category was an important factor. Each dataset underwent a brief statistic analysis, producing a box plot for each category.

The output from the data analysis was presented in Figure 67. The figure indicated that the medians for all three categories were similar (63kWh/m²) and suggested that there was little difference in total annual energy consumption. When compared to the energy performance benchmarks shown in section 2.6.2.2, it was established that the collected dataset appeared to include high energy consuming schools. The median results were taken as the ‘typical’ benchmark, and compared with the ‘typical’ benchmarks found in section 2.6. In terms of the primary schools, the published typical benchmarks ranged from 34-65kWh/m², and in comparison, the collected database benchmarks are situated at the very upper limits of the primary benchmark range. The published ‘typical’ high school benchmarks range from 20-39kWh/m², almost half the value for the collected high school benchmarks (63kWh/m²). The differences between the collected dataset benchmarks, and the ‘typical’ benchmarks were determined as being differences in dataset size and sample.

When the 25th and 75th percentiles as well as the maximum and minimum values were compared, variations between each school category dataset were identified. The variations were determined as being the result of the varying size of each individual database. The variation increased as the number of schools in each database decreased. If the number of high schools within the database was increased, then the variation, in terms of the 25th and 75th percentiles would most likely increase. It was unknown from the published benchmarks what percentiles represented the ‘Good’ and ‘Bad’ benchmarks; hence a comparison could not be made to the collected benchmarks.

The electrical energy benchmarks determined from analysing the collected school data indicated ‘typical’ values that were greater than the published benchmarks in the case of high schools, and just within the ‘typical’ range for primary school. The results demonstrated that there is considerable variation, as demonstrated by the 25th, 75th and maximum/minimum values, within each school type. The variation between the published and collected ‘typical’ benchmarks highlighted the potential hazards of relying solely on published energy performance benchmarks. A building owner or designer could select a ‘typical’ benchmark for a high school using the published benchmarks and it could, as demonstrated by the results, be approximately 50% over/under the true value. Ideally more accurate energy performance benchmarks are needed, that represent a wider range of schools.

To determine why there was a significant difference between the published and collected benchmarks (especially the high school benchmarks), the annual normalised

energy consumption for each school was plotted and several published benchmarks compared.

6.1.5 High School Energy Benchmark Comparison

The comparison of the annual normalised energy consumption of each high school against the known published benchmarks revealed several outcomes (see Figure 68). The data from both the high schools and specialised high schools were combined for the analysis. There appeared to be no separate benchmark data available for specialised high schools. Due to the specialised schools still being classed as high schools, it was deemed acceptable for specialised high schools to be analysed as standard high schools. This lack of representation (for specialised high schools) further highlighted the issues with published benchmarks, and in turn, their lack of complete school categorisation.

The high schools (including the specialised high schools) had annual energy consumption ranging from 30-213kWh/m². Several benchmarks were chosen for the high school comparison, to demonstrate the variability between each classification (i.e. ‘Good’, ‘Typical’) and the variability between each of the published benchmark sources. The ‘Good’ benchmarks ranged from 20-29kWh/m² and the ‘Typical’ 30-39kWh/m². The results demonstrated that none of the high schools lay within the ‘Good’ benchmarks, and only one school, school 21, lay within the ‘Typical’ benchmarks. This result indicated that the published high school benchmarks (see section 2.6.2.2) do not represent the majority of the collected high schools. It could be argued that the collected high school data may be sampled from only high energy consuming schools, or ‘Bad’ schools. However, the variability within the annual energy consumption suggested that the sample of schools, although small, was still suitable.

The results also demonstrated that there were several schools that had an annual energy consumption that far exceeded both the published energy benchmarks, and the majority of the remaining schools energy consumption. These identified schools, schools 7, 17, 43 and to a lesser extent 20, had annual energy consumption over 900% larger than the lowest ‘Good’ benchmark (20kWh/m²) and approximately 500% larger than the highest ‘Typical’ value. Previous analysis sections, also highlighted these schools as having substantial energy consumption. The schools were all, bar school 20, identified as having electric heating (space or storage). This finding further highlighted the limitations of published energy performance benchmarks, as none of the benchmarks found in Table 3 (see section 2.6.2.2) differentiated between heating types

(electric or fossil fuel). Ideally a separate benchmark table should be constructed for schools that utilise electric heating, and hence a separate comparison made between fossil fuel schools and electrically heated schools.

School 20, although not identified as a school with electric heating, was unique in comparison to the other high schools. The school is part of a larger community complex, which includes a sports facility, public swimming pool and library. The supplied electrical energy data was recorded from the meter that supplies all these additional facilities. These additional facilities would impact on the total energy consumption of school 20, and result in it having a higher consumption than a school of similar age and size. A further development to the benchmarks could be the inclusion of these additional facilities.

6.1.6 Primary School Energy Benchmark Comparison

A similar benchmark comparison applied to the high schools was applied to the primary schools in the collected database (Figure 69). A similar outcome was observed (when compared to the high schools), in that only one of the primary schools lay within the published benchmarks. The collected primary schools had annual energy consumption that ranged from 33-143kWh/m². In comparison, the published ‘Good’ benchmarks ranged from 18-25kWh/m² and the ‘Typical’ benchmarks ranged from 28-37kWh/m². The primary school benchmarks are broadly similar to the high school benchmarks, suggesting the buildings exhibit comparable user behaviour, and equipment usage.

The results showed that only one school lay within any of the published primary school benchmarks. This result again questions how representative the published benchmarks are. One issue with the collected database was that there was only 11 schools in the primary school database. In comparison, the high school database consisted of 32 schools. The 11 primary schools may not be accepted as a suitable sample, as the selected schools could all represent ‘Bad’ or high energy consuming schools; hence any comparison to ‘Good’ or ‘Typical’ benchmarks would be unfair. To overcome this issue, the primary school database should be increased to include more primary schools.

The results also demonstrated that there were three schools with higher energy consumption than the remaining schools (and published benchmarks). The identified schools were schools 14, 40 and 41, and had annual energy consumptions of 193kWh/m², 142kWh/m² and 141kWh/m² respectively. In comparison to the

benchmarks, school 14 had consumption over 400% higher than the largest ‘Typical’ value and schools 40 and 41 had consumptions over 280% larger. Previous analysis determined that these identified schools utilised electric heating (see sections 4.1, 6.1.3). Similarly with the electrically heated high schools, the electric heated primary schools have to be compared with separate benchmarks. Unfortunately, separate energy benchmarks that account for electric heating were not available for comparison.

6.1.7 Initial Analysis Overview

The initial analysis of the collected school electricity database revealed several key results that would assist in further analysis. The first key result was the importance of normalisation. The analysis revealed that normalising by floor area was important, as demonstrated by the moderately strong linear relationship. Construction age as a normalisation variable was also tested, revealing a weak relationship to annual energy consumption. Although there was a weak link between age and energy consumption, the importance of separating pre-2000 and post-2000 schools was established.

The initial analysis also demonstrated the requirement to separate the school data into different categories; primary, secondary and specialised high schools. Each type of school is used differently, with differing education and building requirements and hence varying power needs. This highlighted a major failing of the current benchmarking system, as it groups all schools into a common category. Another key result, and possible failing of the current benchmarking system, was the lack of differentiation between heating types, i.e electric or fossil. As highlighted by the results, there is a considerable difference in energy consumption between the two heating types.

The initial results provided a firm foundation for further analysis. The further analysis of the school data would take into account categorisation, age and heating type, as well as determining why there are differences (if any) in energy consumption between the schools, even after these discussed factors have been accounted for.

6.2 Average Profile Analysis

The initial analysis focused on annual energy consumption and annual performance benchmarks, and demonstrated variability in energy consumption between the schools. This variability was observed between each school category and within each category. To determine why differences between the schools existed, as well as determine how schools demand power, it was necessary to analyse more detailed data. The second stage of the school data analysis moved away from the annual consumption

figures, and focused on half hourly power demand data. The increased time resolution data can show how daily power demand varies throughout the day, week and year, as well as between school type, age and heating fuel type. It should be noted that the data used to calculate the average power demand profiles, had all holiday data removed. In contrast the data used to calculate the annual energy consumption (in the initial analysis) contained all holiday data (all 365 days).

The average daily power demand profiles (representing an average of all days bar holidays) for each school was calculated (see Figure 71). The plotting of all the school average demand profiles demonstrated the variability of each profile, in terms of peak demand, baseload, and general demand shape (sharp peaks and broad peaks). The average demand profiles were separated into two categories based on how the profiles were grouped; typical and atypical. The typical profiles had a common broad peak occurring during the school hours, and consisted of 42 schools. In comparison, the atypical profiles were defined as those that were not grouped with the typical ones, and had fairly unique power demand profiles (large peak demand, large baseload, lack of broad peak, multiple sharp peaks).

The plotting of each school's normalised average power demand profile demonstrated that even after normalisation by floor area, differences still existed between each schools demand. However, the main outcome from the analysis was the identification of the 'typical' broad peak profile shape that was observed in the majority of school profiles. The next stage of the analysis was to investigate the power demand profiles and establish why the differences existed between each profile, or why there was similarity between each profile.

It was decided to select three schools from the database, with one school from each category (although the actual selection within each category was random) for a more in-depth analysis. Each of the selected schools underwent the same analysis, producing average weekday and weekend demand profiles, and average seasonal demand profiles. The various power demand profiles from each school were then compared with each other, determining how the season and weekday/weekend impacted on the power demand of each category of school.

6.2.1 Average Weekday and Weekend Power Demand Profiles

The average power demand for the weekday and weekend was calculated for each of the three selected schools. The two profiles were created to show any potential difference between a typical weekday power demand, and a typical weekend power

demand. It was assumed that the average weekend power demand for the schools would be considerably lower, with either slight rise in power demand (from baseload) or no change in baseload. The demand profiles for each school (Figure 72, Figure 74 and Figure 76) were analysed separately and then compared to each other, to highlight any variance between school (and hence category).

All three schools showed a similar weekday power demand, with a standby baseload, rise in power demand and subsequent drop in power demand over the course of the school day. For the selected high school, school 11 (see Figure 72), the constant power demand that occurred from 09:30 to 12:30 is the result of the building's power demand saturating. The majority of essential systems that are required, are turned on. The power demand steadily drops to 10W/m² at 16:00, as lighting and catering facilities are slowly switched off. At 16:00 the school is closed to the students (school times can vary, but generally shut at or before 16:00).

The constant demand that occurs from 16:00 to 20:30 was associated with the after school usage, and could be related to classroom lighting and even gym hall lighting or outdoor flood lighting. The power demand then drops at 20:30, and returns to baseload by 22:00. It was expected that the school would return to baseload before the school was used after the school hours. It can be assumed that the school was not used directly after the school children have left (at the end of the school day), hence the power demand after 16:00 was a period when the school was not being used.

In contrast, the average weekend energy usage had a smaller power demand and a different shape to that of the weekdays. This was expected, as the school is used in a different way at the weekend, and there are less people using the building. The weekend has a baseload value of 4.8W/m², which was very similar to the weekday baseload. The baseloads are similar due to the same equipment that contributes to the baseload, being on at the weekends. The power demand increased at 06:30 to a peak power demand of 7W/m² at 08:00. The power demand slowly decreases after the peak power demand, and returns to the baseload at 18:30. The peak weekend demand will consist of a mixture of classroom lighting, sports facilities and other small power use. The limited use of the school at the weekends, in comparison to the full use during the week, resulted in a smaller peak at the weekend.

The weekend profile analysis revealed that the time at which the power demand increases from baseload to peak demand, varied between the weekday and weekend profiles. The weekday profile had an increase in demand at 04:30, whereas the weekend had an increase in demand at 06:30. This difference in time of demand

increase is due to how the building is used at the weekends and weekdays. The school is open early on weekdays for teachers (and other staff), as well as students. At the weekends, sports clubs or classes may start later in the morning, hence the power demand occurs later at weekends than weekdays.

6.2.2 *Primary Schools*

The selected primary school, school 39 (Figure 74), had a different weekday and weekend demand from the analysed high school (school 11). The weekday power demand profile consisted of one broad peak, starting at 04:00 (with a baseload of $4\text{W}/\text{m}^2$), reaching a peak demand at 08:30 (with a value of $23\text{W}/\text{m}^2$), and returning to baseload by 18:30. Similarly with the high school, the rise (and subsequent drop) in primary school power demand is the result of heating systems, lighting and small power systems being switched on (or off) during the day.

One difference between the primary and high school, in terms of this initial rise (and fall) in demand. The peak demand of the high school was $15\text{W}/\text{m}^2$, and in comparison, the peak demand of the primary school was $23\text{W}/\text{m}^2$. The peak demand difference between the two categories of school could be due to how each building is used, and in turn how each system is used. The selected primary school is 54 years older than the high school, and may have older, inefficient lighting systems and mechanical ventilation (or heating) systems. The construction of the older primary school may also account for an increased power demand, with heating systems (AHUs) compensating for heat loss as a result in poorer construction standards (possible single glazed windows, solid stone construction, lack of wall/roof insulation). It was originally assumed that a high school would have a larger power demand (peak) than a primary school, based on the assumption that a high school would have a larger equipment list (IT equipment, lighting) than a primary school. In respects to these two selected schools, this was not the case.

Another notable difference between the primary school and the high school was that there is no afterschool usage at the primary school. The high school demonstrated power demand from 16:00 until 21:30, whereas there was no evidence of after school usage in the primary school demand profile. The lack of after school usage was explainable, as primary schools do not generally have the facilities for after school clubs, in comparison with a high school. This accounts for the sharp decrease in power demand that is apparent in the primary school weekday demand profile (see Figure 74).

School 39's average weekend power demand profile had an almost unchanging power demand throughout the 24 hour period. The demand remained at baseload (3.6W/m²) until 04:30 where it is dropped slightly (3.1W/m²), and returning to baseload by 20:30. The slight drop in power demand mimicked the times of the active portion of the weekday profile, (except that the weekend dropped in demand). It was assumed that the lack of after school usage during the week would also be true of the weekend power demand. The lack of an increase in power demand during the weekend confirms this assumption. The drop in power demand during 04:30-20:30, could be due to external lighting being switched off for the daytime.

6.2.3 *Specialised High Schools*

School 17 was selected to represent the specialised high schools. The average weekday power demand profile differed from both the primary and high schools, in that they contained both a broad peak (as found in the primary and high schools), and also two sharp peak demands. The broad peak had occurred from 04:30 to 19:30, and reached a peak demand of 42W/m². This has a high power demand when compared with the primary and high schools. The increased peak power demand could be related to additional equipment for the additional requirements of the school, such as sensory rooms.

The large sharp peak demands occurred from 02:30 to 04:30 and 19:30 to 22:00 on the weekday profile and have peak power demands of 34W/m² and 32W/m² respectively. Originally, these sharp demand patterns were associated with electric space heating. The system appeared to be turned on several hours before the school opens and for a few hours in the evening. It would be expected that if the sharp peaks were a result of an electric space/storage heating system there would have been other sharp peaks occurring throughout the day. However, additional sharp peaks may occur during the day, but may be concealed by the buildings remaining power demand.

When adjusted to kW, the demands had peaks of approximately 55kW. When the school description table was referenced (see Table 5), it was established that the school had a small floor (~1400m²) area, and a small pupil number (55). The 55kW peak could be the result of a series of electric heaters (multiple systems of several kW) being switched on.

The weekend power demand (Figure 76) was similar to the primary schools weekend power demand, in that there was no significant rise in power demand during the day, only a small variation of 2W/m² throughout the day. The baseload demand

(14W/m²) is considerably larger than that of either the primary or secondary schools. The larger baseload could be the result of lighting systems, or heating systems being left on. The school has a swimming pool which would impact on the baseload power demand, due to heating pumps and ventilation. The slight variation in power demand during the day could be due to the swimming pool systems (heating and increased ventilation) not being required to the same extent during the day, as a result of increased outdoor temperatures. Additionally, external lighting may be also switched off during the day (similarly with the primary school).

The weekend profile also exhibited a sharp peak demand, occurring in the later evening (20:30-22:30). Further analysis applied to the specialised high school (school 11) was to determine how the weekend sharp peak, that occurred in the evening, varied at the weekends. The average weekday and weekend power demand profiles were created to represent the typical demand patterns for Monday to Friday, and Saturday and Sunday. One key difference between the weekday and weekend profiles was that the sharp peak had a lower demand at the weekend. This was initially assumed to be due to reduced occupant level in the school, hence a reduced impact on the school systems. However, the sharp demand may only occur on one of the weekend days, and not the other. The sharp demand occurring on only one day would, when the average demand profiles were created, result in a lower peak demand. This issue was addressed by sampling several power demand profiles (both Saturdays and Sundays).

The sharp peak only occurred on a Sunday, and not both Saturday and Sunday as originally expected. The results from the high school analysis revealed that there was considerable demand at the weekends, with the majority occurring on Saturdays. It has already been established that the specialised high school weekend demand is almost non-existent, apart from the sharp peak and baseload demands. The sharp demand occurring on a Sunday further suggests that the demands are the result of electric storage heating. The system appears to operate in the evening and early morning, perhaps due to a cheaper night time tariff. The Sunday sharp peak demand could be the system storing up heat ready for the following school day (Monday).

6.2.4 Seasonal Impact on Power Demand

The three selected schools underwent a seasonal analysis to determine how the changing seasons impacted on each schools power demand, see Figure 73, Figure 75 and Figure 77. It was assumed that the power demands in each season would vary, due to the different weather conditions and user behaviour. It was also assumed that the

winter electrical power demand would be greater than the summer's power demand, due to increased lighting and heating (AHU's, heating pumps). This increased use of heating and lighting is to account for the cooler temperatures and lower global solar radiation. Additionally, spring and autumn would have a power demand in-between summer and winter, due to autumn being placed when the temperatures/solar radiation is decreasing, and spring placed when they are increasing.

The high school exhibited significant seasonal variation in both profile shape and peak demand, with the winter having the largest peak demand ($17\text{W}/\text{m}^2$) and the summer having the lowest peak demand ($13\text{W}/\text{m}^2$). The difference between the seasons also observed in the after school power demand, with the winter producing a peak demand of $13\text{W}/\text{m}^2$ and summer producing an after school peak demand of $6.1\text{W}/\text{m}^2$. The difference in after school power demand (between winter and summer) is due to the outdoor facilities being used more in summer, hence a reduction in power demand associated with the gym halls (changing rooms as well). Additionally, the increased natural light levels would result in a reduced lighting requirement, even during the evening, resulting in a lower power demand in summer.

In contrast, there was minimal seasonal impact on the primary schools, with a variation of $2\text{W}/\text{m}^2$. This peak variation is similar to that of the high schools; however, the shape of the broad peak remains fairly constant in the primary schools throughout the seasons. It was expected that there would be a significant difference between the seasons, especially between the winter and summer months. This was based on the previous stated assumptions on winter and summer energy consumptions and power demand. This suggested that there could be considerable potential power savings to be achieved at this primary school, due to similar power demand regardless of outside (or outdoor) conditions.

The seasonal impact on the specialised school was more pronounced than the other schools, (even the high school). The specialised school conformed to the previous assumptions, with winter producing the largest power demand, summer producing the lowest demand, and autumn/spring producing a power demand in-between. The difference between the peak demands of summer and winter was $33\text{W}/\text{m}^2$, a considerable difference when compared with the other selected schools. This large difference suggested that there was a system (or systems) that were used considerably more in winter (and to a lesser extent in autumn and spring) than in summer.

It can be assumed that the associated system (or systems) related to electric heating, and further evidence of this was the seasonal impact on the peak power

demand. The sharp peak demand had the same peak demand in winter, spring and autumn (if the baseload was removed), however the summer sharp peaks have a much smaller demand. As expected, heating demand would be lower in summer than winter, and if the heating was electric based, then the lower heating demand would have a significant impact on the summer power demand profile. This outcome as well as the results from the weekend/weekday analysis further hinted towards this school (school 17) having electric storage heating.

6.2.5 Overall Analysis

The outcome from analysing the average profiles of the three selected schools highlighted several important issues. The first was that each school had a different power demand, with different baseloads and peak power demand. Additionally, the difference between the school's power demand outside schools hours was also identified. The high school exhibited after school weekday usage, whereas the primary school and specialised schools did not exhibit any after school power demand. This after schools use in the high school (and lack of after school use in the primary and specialised school) was also evident in the weekend power demand. The average profile analysis also demonstrated that not all the schools were impacted by the changing seasons, with the primary schools showing almost no variance in power demand. It should be noted that these conclusions were drawn from the analysis of the three selected schools only.

To determine if the conclusions from the average profile analysis were true across the data set, ideally each school would undergo the same analysis. The outputs from each school could be compared to one and another, in terms of peak/baseload, after school power demand, weekend power demand and seasonal impact.

6.2.6 Selected School Suitability

One point worth noting is the validity of the selected three schools (for the demand profile analysis). One important question to ask is how well the selected buildings represent the entire database. The entire school database was separated into the three corresponding categories, in order to study how the power demand varies in each type. The random selection did not involve studying the average demand of each school (and hence selecting a school based on that study), otherwise the 'random' factor of the selection is redundant. Figure 71 demonstrated that there are several demand profiles that have a similar shape, and several that do not. Examples of these atypical shape profiles were the five outlying profiles. The analysis of these atypical demand

profiles could have provided false conclusions when applied to the dataset (although any conclusion drawn would be correct to the selected schools).

To determine if the selected schools (schools 11, 17 and 39) were suitable for the average profile analysis, the annual energy consumption for each school was compared with other schools in each corresponding category. The previously discussed school benchmark comparison (Figure 68 and Figure 69) were used to determine how the energy consumption of the three selected schools compared with the other schools. The high school had an annual consumption of 69.8kWh/m², and the specialised school 212kWh/m². The high school, school 11, had annual energy consumption close to the median of high schools. In comparison to the collected benchmarks (Figure 67), the school's consumption was marginally more than median (by 6.8kWh/m²). The close proximity to the median suggested that the selected high school was appropriate for the further analysis.

The specialised school had an energy consumption approximately three times the median benchmark for either the high schools or specialised schools. Additionally, school 17 was identified in previous analysis section as having abnormally high energy consumption, due to electric heating. The high energy consumption was considered to be abnormally large in both the high schools and specialised high schools. This indicated that school 17 was not an ideal selection of school, due to the high energy demand, high peak demand, and the presence of multiple sharp peaks. Although the school did not accurately represent the specialised high school database, the analysis did provide information of how an electrically heated school consumes power, and how the demand changes between the weekdays and weekend, as well as the seasons.

The primary school (school 39) had an annual energy consumption of 62kWh/m² and when compared to the collected primary school benchmark data (see Figure 67), school 39's annual energy consumption was the same as the median. This suggested that the school was a suitable selection.

It should be noted, that although the selected high school and primary school were deemed suitable choices (and that the specialised school, although not suitable, provided useful results), the conclusions may not be entirely applicable to the rest of the database. Variations may exist between the schools, especially the older schools that contain a wide range of construction dates, and building standards.

6.3 Distribution Board Data

Analysing the average profiles of the three example schools revealed that there were differences in power demand shape and peak and baseload demand. During the analysis of the profiles, several assumptions were made to establish why certain shapes in power demand and power events occurred. These assumptions included the power demand change when key systems, such as heating and lighting, were switched on and off. Additional assumptions were made to explain the differences between the seasonal power demands, especially between the summer and winter average power demand profiles. The assumptions included the lighting systems being used more frequently (and for longer) in winter, as well as heating systems being used less in summer. To test several of these assumptions, more detailed power demand data was required. This detailed data came in the form of distribution board demand data.

The analysis of the distribution board data allowed a deeper insight into how and when power demand varied, and additionally the associated systems that resulted in this demand. This detail on what systems are being used, and when, was missing from the total power demand data. The sample day, see Figure 78, was randomly selected from the weekday data.

Four time points were selected (03:30, 07:30, 10:30 and 15:30) to represent the key events in the demand profile; the baseload, the initial rise in demand, the peak demand and the fall in demand. The demand from the various distribution boards for each of these time periods were analysed and the contributing boards identified.

It was established that the baseload was for a mixture of systems, including lighting and pool related systems. Over 40% of total power demand in this time period (and for the entire baseload time period) was related to the swimming pool relating to heating the pool and the pool room. Other baseload demand related to general power demand, including some school lighting and power socket use. The main difference between the baseload and the initial rise in power demand was due to an increase in mechanical ventilation, some initial occupant related power demand, such the library systems being switched on, and the administration office being in use. There was also a decrease in power demand from the external lighting board, due to the outdoor lighting levels being sufficient. It is most likely that the external lighting systems are on either a timer or light sensor, and unlikely to be manually controlled.

The change from the initial rise to peak demand was the result of key distribution boards having an increased power demand, such as the ‘General’ and ‘MPC1’ boards. The peak demand is also due to several occupant dependant systems being used. As the

school occupant level increased, and as school lessons to commence, the power demand for classrooms and facilities increased. This can be seen in the rise in demand from the library (Lib), technological studies (Techcraft), IT classrooms (ITIC), games hall (GA_hall) and home economics (HE1). With the rise in occupancy in the school, the demand for the various AHUs also increases, with the largest demands being related to the Mech2B, MPC1 and MPC2 distribution boards. The ‘general’ demand, if assumed to be related to general lighting and power sockets would also increase due to this increase in occupancy.

Lastly, the fall in power demand from the peak and back to the baseload, was established to be primarily the reduction in power demand from the various distribution boards. At 17:30 (the time point when this data was taken), the school would have a very low occupancy, due to this time being outside school hours. Only teachers and janitorial/cleaning staff would be present at this time of day. The low occupancy results in a lower requirement for heating resulting in a lower demand from each of the AHU boards (Mech2B, MPC1 and MPC2). Another impact of low occupancy is a lower power demand from the various departments (mainly classrooms and facilities). This can be observed by focusing on the department associated power boards, such as the library, IT classrooms and ‘general’ lighting and small power.

The results from the analysis highlighted that the main change in power demand was associated with heating (in terms of AHUs) and lighting/power sockets in numerous departments.

A further development of this analysis would be to analyse the data in a similar way the sample schools were analysed. It has been established that two of the three sample schools were impacted by the different seasons. Introducing a seasonal analysis to the data could determine where the differences in power consumption between the seasons existed, and hence identify which systems contribute to that change. The seasonal analysis would have to be carried out on sample days in each season, as opposed to creating average demand profiles, in order to retain the demand detail. This additional analysis would also confirm the assumption that the difference between summer and winter power demand is related to the amount of lighting and heating required to compensate the changing light levels and outdoor temperature.

As with the seasonal analysis, the additional data could determine the main power demand differences between a weekday and a weekend. This could help highlight whether the main changes are occupant related, and identify any potential power wastage. The analysis could be carried out on distribution board data for a range of

schools such as primary/specialised, electrically heated schools, and also other buildings (offices). This analysis by category could help explain several of the differences in the peak demands, baseloads and general profile shapes between the high, primary and specialised high schools. Lastly, the reasons or systems that resulted in atypical profile shapes, or demand that could not be explained by the average profile analysis (such as the sharp demand patterns present in school 17's profiles) could be determined (assuming the data was available).

6.4 Office Analysis

The analysis methodology applied to the school database, was applied to the office database. One difference between the two databases was that the office database was considerably smaller. Although the office database only consisted of two office buildings, each office had different characteristics. Office 1 was a 1960's constructed, seven storey building (floor area of 12220m²), with mixed energy efficient lighting energy efficient lighting and standard incandescent, and single glazed windows. In contrast, office 2 was a 2007 constructed, low energy (as BREEAM rated) office (with a floor area of 20,717m²), with energy efficient lighting and heating/cooling systems. The analysis would determine how these two very different offices demanded power. Ideally, two (or more) offices of similar age, size and construction could be compared to establish if any conclusions gained were applicable against the wider buildings stock. Having offices of different age, size and construction gives the opportunity of examining how the power demand varies between each of these factors.

Before any analysis could be applied on the office electricity data, it was necessary to establish the typical working routine of the offices. It was previously established schools are open for ~295 days of the year, or only 191 if excluding weekends. In contrast, office buildings are used for a larger number of days in the year, as employees can have holidays and the office can still be open (excluding national holidays such as Christmas, when the majority of buildings will completely closed). Additionally there are no 'half days' in a working week in offices unlike the schools. Due to the office having less 'closed days' (in comparison to schools), the data cleaning of the office data was a straightforward exercise. The main data cleaning involved removing national holidays (bank holidays, Christmas holidays) and to separate the data into weekdays and weekends.

6.4.1 Office Benchmark Comparison

It was originally assumed that the larger office (office 2) would have a greater annual energy consumption than the smaller office (office 1), regardless of the low energy characteristics of office 2. The annual energy consumption of each office was calculated, and a comparison made between each office and to the published office benchmarks found in Table 1, see section 2.6.2.1. The results demonstrated that the annual energy consumption of office 1 was higher than office 2, with a difference of 49kWh/m². The lower energy consumption of office 2, was the result of more energy efficient measures (such as lighting) and improved building/construction standards. As discovered in the distribution board analysis, a large proportion of power demand (and hence energy consumption) in the school was associated with AHUs.

If it is assumed that a similar proportion of power demand associated with heating/cooling in the offices, then a better constructed (in terms of insulation, double glazing, general improved construction standards) office 2 may have a lower heating requirement, hence lower energy consumption. In comparison to the annual energy consumption of the schools, the offices appear to have similar consumption to the five identified high energy consuming schools (electric heated). However, office buildings generally have a higher intensity of IT equipment (PC, servers), and possibly air conditioning that could account for this difference.

The annual energy consumption of offices 1 and 2 were compared with several of the energy performance benchmarks found in Table 1, see section 2.6.2.1. The results demonstrated that the offices were situated below the ‘Good 3’ and ‘Typical 3’ benchmarks, representing a large air conditioned prestigious building. One pronounced difference between the performance benchmarks provided for office buildings Table 1 (see section 2.6.2.1), and the school benchmarks (Table 2, Table 3, see section 2.6.2.2), that basic construction and usage details were accounted for.

Office 1 is a multi-storey office with a mixture of natural and mechanical ventilation, and fits into the second category of Energy Consumption Guide (Carbontrust, (2003)) benchmark (naturally ventilated open plan). In contrast, Office 2 is a modern built partially air conditioned building, with large windows and open spaces, and could be classed within the fourth category of Energy Consumption Guide (Carbontrust, (2003)) benchmarks (air conditioned prestigious). For office 1, the benchmark for the naturally ventilated open plan office was between 54kWh/m²/yr and 85kWh/m². In comparison, office 1’s energy consumption is considerably higher than the benchmarks. In comparison, as shown in Figure 80, office 2’s energy consumption

falls below the ‘prestige’ benchmark, i.e. the fourth set of office benchmarks. The lower total annual energy consumption of office 2, in comparison to the ‘prestige’ benchmark, could be due to either the building being considerably energy efficient, or the building lacking the same level of air conditioning as the office benchmark.

6.4.2 Office Average Weekday and Weekend Profile Analysis

Similar with the school analysis, the investigation moved away from comparing annual energy consumption data, and focused on half hourly power demand to highlight key features of each offices power demand data.

Analysing the weekday profile of Office 1, the baseload was 14.4W/m² (or 180kW) and remained fairly constant until 05:30. This baseload can be compared with the three analysed schools, which were 5W/m², 3.6W/m² and 16W/m². Only the specialised school, or school 17, has a higher baseload than office 1. The weekday demand profile had a broadly steady increase in power demand in the morning; however the decrease in demand (after the peak) had several stages or steps. These steps or changes were due to certain systems being switched off at staggered times. It was discovered that office 1 had several areas of the building that dealt with the public. These sections had different, and shorter, operation hours than the rest of the office. This resulted in the building have several stages of decreasing power demand. Additionally, the office had a dedicated catering department that closes after lunch time.

There was a slight rise in weekend power demand (from a baseload 14.4W/m²) to a peak demand of 19W/m² at 09:30. The marginal increase in demand is related to the parts of the building that are open to the public. It could be argued that the average weekend demand is lower than the real power demand, due to averaging errors, such as the ones found in school 17’s analysis. On further inspection, it was discovered that the weekend demand occurred on both Saturdays and Sundays, coinciding with the opening hours of the office. The identical weekday and weekend average baseload demand suggested that the building’s systems (that contribute to the baseload) are used in a similar way i.e. are not weekday/weekend specific.

The high nature of the baseload and peak demand (in comparison to the schools for instance) could also be the result of the building containing large IT servers/mainframes. In section 2.9.2.4, it was established that a mainframe/server can demand 40,000-140,000kWh/yr, which represents 4.6-18% of the baseload or 1.55-5.7% of the peak demand. Although the mainframe will be constantly on (and hence

can be counted as baseload) increased user activity throughout the day would result in a subsequent increase in power demand.

Office 2 had a weekday power demand that consisted of a single broad peak with a baseload of $9.8\text{W}/\text{m}^2$ and a peak demand of $35\text{W}/\text{m}^2$. There appeared to be three clear rises in power demand in office 2 over the period 01:30 to 12:30. The first increase in power demand 01:30 to 05:30 with a power demand rise from $14\text{W}/\text{m}^2$ to $16\text{W}/\text{m}^2$ ($2\text{W}/\text{m}^2$ difference). This could be accounted by the heating system switching on and electric heating pumps and associated AHU being activated. The second rise in demand occurred from 05:00 to 06:30, and with the demand change from 14 to $16\text{W}/\text{m}^2$ ($2\text{W}/\text{m}^2$ or 41kW difference).

The second rise could be the result of lighting systems being switched on, the cafeteria equipment being switched on, plus additional ventilation being used. The third rise in power demand from $16\text{W}/\text{m}^2$ to the peak demand of $35\text{W}/\text{m}^2$ at 12:30 could be associated with the increase in IT usage, lighting, heating/ventilation, and other systems being switched on as employees start entering the building (same systems as seen in schools and other offices). The power demand then dropped from its peak value of $35\text{W}/\text{m}^2$ to baseload value from 12:30 until 21:30, as systems in the building were slowly switched off.

The weekend power demand was only marginal (similarly to office 1), with a rise in $3\text{W}/\text{m}^2$ against the baseload. The small rise could be associated with weekend cleaning staff, or a small number of workers occupying a small section of the building. The similar baseload between the weekday and weekend profile of office 2 (similarly with office 1) will be due to the same systems being in standby (or constant use) during the week and weekend.

6.4.3 Seasonal Impact on Office Power Demand

The office data underwent seasonal analysis to determine the impact of the changing months on the power demand of each office.

For office 1, the spring and winter had similar power demand profiles and an almost identical peak demand. It was assumed that the office would have had a considerably larger winter demand profile in comparison to the other seasons. This assumption was based on the building being an old multi-storey office, with old single glazed windows; hence the heating requirement would be considerably higher than spring and autumn. The similarity between spring and winter, would suggest that the power systems and occupant behaviour does not appear to change. When the seasonal

profiles are compared together, it can be seen that the profiles have almost the same baseload values, and all but winter have the same initial rise time (05:30). The initial rise in power demand for the winter profile appeared to occur an hour later. It was expected that the winter demand would occur at the same time as the other profiles, or even slightly before, as heating and lighting was used earlier in a winter day in comparison with a summer day.

Lastly when analysing the decreasing power demand from 11:30 onwards, it was discovered that the step decrease in power demand was more apparent. Focusing on the summer profile, the step in power demand can be seen occurring at 17:30. In comparison to the average weekday profile shown in Figure 81, the decrease appeared more predominant. It should be noted that this set in decreasing power demand is also clearly visible in the other seasonal profiles. The step could be a result of the lowered power demand that occurs during summer. The average demand profiles demonstrated that there was a slow drop in power demand from the plateau to the baseload. The step drop in power demand, as shown by the summer profile, may be masked by the switching off of the building's other systems. If in summer, these other systems are not being used then they step drop in power demand would not be as masked.

In comparison, office 2 had a different seasonal impact on its average power demand. It also appeared that the summer and autumn profiles have a similar power demand as each other, as well as spring and winter having similar profiles.

The peak power demand of the spring and winter profiles were 33W/m^2 and 32W/m^2 respectively, and the baseloads were 9W/m^2 and 10W/m^2 . One difference between the spring and winter profiles, was that although they did have a similar shape of power demand, the increases/decreases in power demand varied. The peak power demand for spring occurred at 11:30 whereas the peak demand for winter occurred at 12:30. One difference between the profiles was that the baseloads were slightly different (by 1W/m^2), and additionally there was a difference of 2W/m^2 in the evening baseload. Similarly to the analysis of the school data, seasonal changes in the baseload could indicate that there are systems that contribute to baseload that are influenced by seasonal change (lighting, heating, etc).

In comparison to the spring and winter profiles, the summer and autumn have an almost identical demand profile. The baseloads of summer and autumn were 9.8W/m^2 and 10.4W/m^2 , and the peak demands were 38.7W/m^2 and 38.4W/m^2 . The peak demands occurred at the same time, 12:30, which is consistent with the winter profile. Both the summer and autumn demand profiles have the same gradient of decreasing

power demand, and subsequent fall to the same returning value by 21:00. One key difference between the two groups of profiles was that the initial step in power demand that was identified in the average daily demand profile (see Figure 84), was visible in the summer and autumn profiles only. This suggested that the systems that result in this shape of power demand had to be seasonally affected. The step in power demand was slightly visible in the spring profile, however not to the same extent as the summer and autumn profiles.

One possible reason for this step shape of power demand is that the building incorporates a chilled beam cooling system. The chilled beam system uses cooled water that is pumped round a building via ceiling pipes. This system is an alternative to HVAC systems. The step in power demand being present in summer and autumn (and slight use in spring) and not winter, would suggest it could be a heating/cooling system. However, due the power demand occurring in the early morning and not during the day it may not be related to a cooling system.

The outcome of the seasonal analysis determined that the winter demand was considerably lower than the summer demand. This outcome was the opposite of the results from the other building's seasonal analysis. It has always been assumed, that the winter power demand will be higher than summers, due to increased light and heating (both in terms of lighting time and amount of lighting). The increased demand could be the result of an increased use of air conditioning to maintain a cooler indoor temperature. However there would have to be substantial amount of air conditioning in the building to produce such a difference between the summer and winter demand profiles. Without distribution board power data, any reasons for the difference are just assumptions.

6.4.4 Overall Office Analysis

The analysis of the office data provided a useful insight into how the two office power demands varied from weekday to weekend, and from season to season. The results first indicated that office 2, although a larger office, had the smaller total energy consumption. This difference in consumption was also present when the average power demand were analysed. The peak weekday demand for office 2 was 8W/m² smaller than office 1, and between 5-10W/m² smaller seasonal difference between Office 2 and Office 1.

The seasonal analysis also indicated that the assumptions regarding winter demanding more power than summer (as made in the schools analysis) was not

applicable to the offices. Instead, it was established that office 1 had summer as the lowest power demand; however it was both spring and winter that had a highest power demand. For office 2, summer and autumn had the highest power demand (and similar shape in demand, with spring and winter having the lowest power demand (and similar shape). This highlighted the importance of determining if the buildings incorporate air conditioning or mechanical ventilation.

It should be noted that the outcomes of the office analysis may not be completely applicable to other office buildings. The variance within the office building stock is very large, as demonstrated by the numerous benchmarks that are available. The office data would benefit from being expanded to include a wider range of office buildings, in terms of construction dates, floor size and heating/cooling type, and hence determine how applicable the conclusions gained from the analysis were.

6.4.5 Weather and Power Analysis: Temperature

One advantage to the office database (over the school database) was that local weather was also available. It has been assumed that the thermal demand will increase as the outdoor temperature decreases, due to heating systems being used more. But the actual impact of temperature, and other climate variables on electricity is not known.

In terms of thermal (or gas demand) any increase of the heating systems would result in a noticeable change in demand. It was also assumed that a rise in heating demand would result in an increase of electricity demand, due to electric water pumps, chillers and AHU's. The analysis of the temperature data against the power demand data aimed at indicating the impact the changing temperature, if any, on the electricity demand.

The lack of a substantial trend between the outside temperature, see Figure 85, and the power may be due to the selected data. It has already been assumed that any increase in power demand during the winter could be the result of heating systems. The heating system can be used throughout the year and possibly with the heating pumps running for a longer period in each day. The time when the heating is used most can be defined as the heating period. To determine whether or not a trend can be found in data taken from the heating period, a sample within this period was selected and analysed.

One issue occurred before attempting to analyse the smaller data set. When the seasonal power demand profiles for office 1 and office 2 are investigated, determining where to sample the data proved difficult. Office 1's seasonal plots, see Figure 82, demonstrated that the winter and spring power demand was high than that of summer.

A sample of data could be taken from either winter or spring. Office 2's seasonal power demand profiles, see Figure 84, demonstrated that the highest power demand was in the summer and autumn months. As already stated, this suggested that the building has an increased cooling demand in summer/autumn opposed to an increased heating demand in winter/spring. There could be an increased heating demand in winter/autumn, however it appears that the possible cooling demand far exceeds it. The same methodology can be applied to the cooling load for office 2 as the heating load in office 1, with a data sample taken from the summer/autumn months.

The results did show that for office 2, a higher outside temperature did result in a higher power demand (as indicated by the slight trend). This would be consistent with the power demand associated with office 2's cooling system (chilled beam, as well as some air conditioning) being used for longer periods to compensate for the warmer outdoor temperatures. In contrast, office 1 did not exhibit any trends and is consistent with the office not having any cooling systems (instead mechanical ventilation). Instead this suggested that office 1's power demand was more influenced by lighting and other systems.

It should be noted that there is an issue with the analysis of the outdoor temperature and the associated building power demand. There can be several instances where the building's heating/system can be active regardless of outdoor air temperature. This could be a result of poorly set up energy management systems, or outdated/limited temperature controls. If the heating/cooling systems were used throughout the year, and the main difference between the summer and winter demand was a slightly longer heating/cooling pump use, then a proper trend may be hard to identify.

6.4.6 Weather and Power Analysis: Global Solar Radiation

It was additionally assumed that the amount of natural light entering the building (or available) would be linked to the amount of artificial lighting used within the building. To determine if there was a significant link between the outside light levels (or global solar radiation), the light levels were plotted against the corresponding power demand.

The same issue of selecting the correct sample of data as discussed in section 6.4.5, was also applicable to the global solar radiation data. It has already been assumed that during the winter more artificial lighting will be used than in summer. This could be defined as the lighting period. A sample of data from the lighting period (December) was processed to determine any link between the light levels and the power demand.

Unlike the temperature analysis, it can be assumed that there is only one lighting period that is applicable to both office buildings. For both offices, the data from December was analysed and linear regression equations calculated.

The increase in R^2 value, as a result of reducing the dataset, indicated that by selecting a period where the use of artificial lighting should be higher (than the rest of the year) resulted in a stronger trend between light and power.

However, the results for both the full dataset and the select dataset indicated that an increase in the global solar radiation results in an increase in the buildings power demand. This result is contrary to the expected outcome that the power demand should increase as light levels decrease. If it is assumed that the varying power demand throughout the year was associated with artificial lighting, then the results indicated that there is an increase in lighting demand when the natural lighting levels are high. These high natural lighting periods would most likely be during the summer.

One key difference between analysing the full global solar radiation dataset (Figure 87) and the reduced, or lighting period, dataset (Figure 88) was that there was an evident gap in values present in the reduced dataset. This gap appears from ~200kW to ~400kW for office 1 and from ~350kW to ~550kW for office 2. The reason for this gap is that it represents night time power demand, shown by limited/non-existent global solar radiation. The reason for the gap occurring in-between the scatter points is due to the varying power demand and light levels throughout the day (i.e. early morning demand, with increasing light levels), as well as the inclusion of weekend power demand. The weekend power demand is lower than weekday demand, however the global solar radiation would be very similar (if not identical) to the weekdays. This results in scatter points with high global solar radiation, occurring at relatively low power demand.

The identified gap was noticeable in the reduced dataset because the data represents only one month; December. The global solar radiation will be similar across this month, as well as the buildings power demand. Global solar radiation varies throughout the year and hence, by analysing a twelve month period this variance in solar radiation is accounted for. Additionally, previous analysis determined that each office had a different seasonal impact on its power demand. The changing seasonal power demand, as well as the varying global solar radiation would effectively fill in the identified gap in (and hence produce Figure 87).

Similarly with the temperature/power analysis, the results should be noted with caution. Artificial lighting can be controlled either automatically, by user interaction, or

a combination of both. There could be several instances where lighting is used when not actually required, due to inaccessible lighting controls (or automatic systems) or user preferences. The falling light levels may not necessarily result in the use of lighting within a building.

6.5 Thermal Demand

The analysis changed focus from electrical demand data and investigated the thermal demand of buildings. Several issues arose before the gas demand data could be analysed. The first was that there were only a small number of buildings within the thermal database. Several of these schools were also not apparent in the electrical school database resulting in key information, such as building age and floor area not being initially known. Another problem with the thermal database was that there were very few schools within in the predefined school categories; only 4 high schools and one primary. For a fairer comparison, several more schools would have been required in each category to determine reliable conclusions.

The second issue with analysing the thermal database was due to the nature of the collected data. The majority of data collected was in actual gas usage, in m³ and one school's data was in kWhs. For comparison, the school data had to be normalised in terms of one unit. For either converting into kWhs or back to the metered (m³) data, the efficiency of the boiler has to be known. Ideally the actual gas usage would be converted into kWhs to allow a comparison to the school energy benchmarks (Table 3, see section 2.6.2.2). All the school thermal data (in m³) was converted³ into kWh.

Another potential issue with analysing the gas usage data was understanding how the data was recorded. As discussed previously, (see section 3.2) the gas usage data is the output from monitoring the gas meter. This meter was on the main gas line, hence represents the total amount of gas being fed into the building. To analyse the thermal demand, or the energy required by the boilers to heat the school, only the boiler gas usage data should be analysed. This was difficult to achieve as the metered data not only represents the boiler usage data, but other gas usage data, such as the kitchens and labs. To overcome this issue, it was assumed that the majority of the metered gas demand relates to the heating boilers (and any other usage ignored). Lastly the gas data supplied for several schools did not encompass an entire year, only nine months. This was due to several of the studied school being opened for less than a year (when the

³ Converted using www.ukenergy.co.uk

data was supplied), or that the schools have only started monitored their gas usage at a half hourly resolution (opposed to monthly or quarterly) within a nine month period.

6.5.1 Sample Profile and Average Profiles.

It was expected that the building would have had no baseload gas demand, based on the assumption that the heating systems, as well as any other gas based system, would be switched off outside the school hours (or mainly at night). Analysing the sample demand profile demonstrated that the school had no baseload unlike the power demand. The gas demand outside the main active portion could have a slight gas demand such as a pool heating system. The lack of a baseload would suggest that the school has a very efficient energy management system and gas is used only when required. One point to note, on further investigation it was established that this school had a swimming pool or not. The lack of baseload associated to the pool could be the result of a heat recovery system, or the use of an electric pool heater.

The sample profile (see Figure 89) demonstrated that the building has zero gas demand until 01:30 when the gas consumption rose to 655kWhs. When this profile was compared with the corresponding power demand profile, the initial thermal demand coincided with the one of the rises in power demand. In terms of the power demand profile, this is due to the heating pumps and associative AHU's. This could have been the result of the heating system being switched on, although this appeared to occur quite early in the morning than was expected. The demand then increased to 966kWhs at 03:30, and decreases to a steady demand of 644-660kWhs. At 06:30 the demand slowly began to reduce, with the occasional demand spike occurring at 13:30 and 15:00. At 16:30, the demand was only 177kWhs, and this point could be considered the end of the school day. The gas demand then increased to 244kWhs by 19:30, and fell to 111kWh by 20:30. There was a final spike in demand that occurred at 21:30, followed by the gas demand returning to zero at 23:00. The demand from 16:30 to 23:00 can be associated with after school building use (after school clubs). The lower demand suggested that only parts of the school were heated in comparison to the full school.

The main active demand had three identifiable sections, an early morning section (01:30 to 09:30), an afternoon section (09:30 to 16:30) and an evening section (16:30 to 23:00). The morning demand is the result of school boilers heating up the school (and possibly the pool) before the school is opened. The second stage in demand could be the result of the boilers maintaining the school temperature (opposed to heating the school up to the temperature), and due to the increasing outside temperature, there

may be a smaller demand for additional heating. This section of demand could also contain kitchen gas usage and lab usage. The last section of gas demand is the result of after school usage.

On first inspection, it was apparent that there was a significant difference between the weekday average weekday gas demand and the average weekend gas demand, similar to the power demand. There was still considerable weekend gas consumption (in comparison to the weekday), suggesting there was school usage at the weekend. One difference to the average profiles presented in Figure 90 and the sample day profile presented in Figure 89, was that the average profiles exhibit a baseload. The sample profile had no baseload, with the active demand returning to zero outside the school times. The average weekday profile had a baseload of 51kWhs and the weekend demand profile had a baseload of 46kWhs.

The presence of a baseload in the average profiles implied that there were days when there was a sizable baseload (in order to still be present in the average profiles). At this stage of the analysis, it could be assumed that days with a baseload are due to high gas demanding days (or days with high heating requirements). This could be primarily associated with winter school days.

The peak demand of the average weekday profile occurred later than the sample day. The sample day had a large demand spike at 03:30 and was assumed to be the building using gas boilers to heat the school up to the preset temperature. A sharp peak does not exist in the average profile, although it could be assumed that the sharp peak (at 08:00) could be a large heating demand. The large demand spike (in the sample day profile) may occur at different times of the day, as well as different peak demands. The variation in peak demand, or the large heating spike, would be averaged out when creating the average profiles. The shape of average weekday profile implied that if it was representing an actual day, then it would occur when the school had a low heating demand. The peak demand is approximately half of the sample day peak demand, and the late occurring peak demand suggested that the heating was required later than on the sample day.

The average weekend profile had a peak demand of 283kWhs and had a shape very similar to the average weekday profile. The main difference between the two average profiles was that the sharp peak demand, as well as the other general demand was lower for the weekend profile. It appeared that the same system (assumed to be the heating boilers), caused the same demand peak at 07:30 in the weekend profile as the weekday profile.

The average gas demand profile analysis indicated that there was a substantial difference in demand, when the weekday and weekend thermal demand profiles were compared. To gather further information on how gas is used in a school, the average demand profiles were then separated into seasonal profiles. Although the seasonal profiles are still averages, the profiles will be more accurate in portraying how gas demand varies than a annual profile.

6.5.2 Seasonal Impact

The average seasonal gas demand profiles indicated that each seasonal profile had a different peak demand and baseload. As with the average daily demand profiles, the seasonal gas demand appeared to have a baseload (opposed to the lack of baseload shown by the sample day profiles). In terms of peak demand, it was anticipated that the winter demand would be higher than the spring and autumn demand, due to the reduced outdoor temperature and hence increased heating demand. It was also expected that the peak power demands, and general demand shape, of the spring and autumn demand profiles would be similar. This expectation was based on the results from analysing the power demand analysis, (see section 4.2).

One similarity between the spring and autumn profiles (see Figure 91) was the after school gas demand. Both seasonal demand profiles demonstrate the gas demand dropping from peak demand (06:30/08:30) and levelling slightly before finally decreasing. The levelling demand occurred at 16:30 in both seasonal profiles, and would be related to the school beginning to close for the students, but also preparing for the evening use. One key difference between the autumn and spring profiles was the time that the peak demands occurred. The spring demand occurred at 06:30 and the autumn peak demand occurred at 08:30. This suggested that the school required heating earlier in the spring months than the autumn months. However, the larger peak demand of the autumn profile then suggested that although the heating demand was later, it was more substantial.

The winter gas demand profile shape has similar traits to the other seasonal gas demand profiles. In terms of shape, the winter demand has similar properties to the autumn demand with the peak demand occurring at the same time. The initial demand of the winter profile was unlike the other seasonal profiles, as there was a sharp rise in demand as well as an initial levelling of demand. The demand increased from the baseload until 02:30 and then the gas demand levelled out at ~325kWhs until 05:30. The other seasonal thermal demand profiles do not have this initial gas demand that was

present in only the winter months. If the school has a series of boilers (instead of one boiler), the school could use just one to initially heat the school slowly. When the heating requirement became more urgent, then the other boilers could be switched on resulting in a larger gas demand. The increased thermal demand at winter confirms the expected outcome of the heating system(s) being used more due to the cooler outdoor temperatures. Ideally the comparison between the low summer thermal demand (due to expected warmer outdoor temperature) and the winter demand would reinforce the demand differences.

6.5.3 Profile Comparison

The five gas demand profiles were presented in Figure 92 were normalised by the corresponding school total floor area. It was evident that in each school, the profiles demonstrated slight similarity, in terms of shape. When thermal schools (TS1-TS4) were compared, it was established that several traits were present in the three gas demand profiles. The first obvious trait was the rise in demand to a peak demand that started in the early morning. A rise from baseload in the early morning may be assumed to be a standard trait across any gas demand profile, however this is disproven by TS5's demand profile (with its decreasing demand in the morning). The second common trait found in the gas demand profiles, is that they have a notable peak demand that occurs at approximately the same time. The peak demand occurring at approximately the same time in each school could be considered as part of a 'typical' or 'generic' profile.

TS5 had a different gas demand profile, when compared to other average gas demand profiles in the database. It appeared to have an inverse demand profile in relation to the other school demand profiles. When the other school profiles had periods of high gas demand, school 5 had a period of relatively low demand (or a baseload). Additionally, when the other schools had a period of falling or little gas demand, school 5 had a period of rising gas demand. It was unclear why this school had such an unusual demand profile, and when referencing the thermal school details (Table 7, see section 3.9.3), a possible difference between this school and the others could not be determined.

6.5.4 Overall Analysis

The thermal demand analysis suggested that the average gas data could be analysed in a similar way to the electrical power data, in terms of average weekday/weekend profiles, and seasonal impact. Additionally, the analysis suggested that there was a common demand shape present in four out of the five selected schools.

The common shape, represented by a broad peak, was evident in each of the thermal demand profiles (bar school TS5), and suggested that ‘generic’ or ‘typical’ thermal demand profiles may be possible. The thermal data is also subjected to the same statistical validity (due to a small sample size) as identified in the electrical database. The similar traits (baseload, peak/broad peak) were identifiable in only four (out of five schools). A sample of only five schools could not represent the entire school building stock, especially when factors like category, construction age, use and whether the school has a swimming pool, are unaccounted for.

The thermal database would need to be increased to encompass a wider range of schools (including new and older schools and school category) and hence determine if the identified ‘typical’ traits were applicable to the wider building stock. Ideally, thermal demand data for the same schools used in the electric power demand analysis would result in both ‘generic’ thermal profiles, ‘generic’ power profiles, and in turn ‘generic’ total energy (thermal and power) profiles.

Chapter 7 DISCUSSION: GENERIC PROFILES

7.1 ‘Generic’ Profiles

The analysis of the databases moved away from processing annual consumption values and average power demand profiles, to focus on identifying trends in all daily power demand profiles for each school. After key trends are identified and key issues accounted for, ‘generic’ power demand profiles can be constructed. However, there are several stages of data processing and analysis required before these profiles can be constructed.

The school electricity database was selected for this additional analysis, due to it containing the largest number of buildings.

7.1.1 *Processing the Data*

There was an initial issue when attempting to plot all school power demand profiles (365 days, for 48 schools), as there were over 800,000 data points for the dataset. When the school holidays were removed from each school, the number of points reduced to over 650,000. Attempting to plot this vast amount of data exceeded the data limits of standard graphing and spreadsheet software. Suitable graphing software was located, and with data point limits in the several millions. However, when the data was plotted, the program continually crashed. Although the database consisted of over half a million points (well within the limits of the program), the nature of the 24 hour profiles resulted in issues. Each time index (00:00, 00:30, etc) had 14,140 data points, quickly overloading the program (OriginLab), when plotting a full 24 hour profile.

To overcome this issue, the data was sampled at various rates to allow the software to plot each dataset. The dataset for all schools and all days (with holidays and electrically heated schools removed), see Figure 93, was sampled at a rate of three. This sample rate was applied to each time index, resulting in every third day being selected for the sampled dataset. For the ‘all school weekday’ (or every single weekday data for each school) data set, see Figure 94, the sample rate was reduced to 2, resulting in every second day being selected for the sampled dataset. The other data sets presented in Chapter 5 (each school dataset) were not sampled due to a lower number of data points in each dataset (allowing the program to process the data without the need for sampling).

It should be noted that although several of the datasets were sampled in order to plot the data, the actual datasets used for the analysis (and creation of ‘generic’ profiles) were not sampled.

The analysed datasets were additionally normalised by floor area, and the schools identified as incorporating electric heating (storage or space) were removed from the analysis. Both the normalisation and the removal of the electric heated schools were to ensure that the data being analysed represented typical power demand of the schools, and that the schools were being analysed as accurately as possible.

The profiles shown in Figure 93, represented forty-two schools, with each school containing 295 twenty-four hour power demand profiles. It should be noted that not all schools had 295 profiles. Due to earlier application of the data organisation program, the databases underwent numerous filters, to adjust for half days, time correction and to remove unwanted/abnormal profiles. The removal of the unwanted and abnormal profiles, and removal of the half day power demands, resulted in several days being removed from the schools. The remaining demand profiles (over 5000 after sampling the data set at a rate of 3, see Figure 93) produced a common broad peak, with a starting time from 03:30-06:30, and a finishing time from 15:30-21:30. Figure 93 also indicated that there were several demand profiles that had a very low and unchanging power demand not removed by the previous filtering processes.

The low and unchanging power demand was found to be related to weekend power demand. The analysis of the average profiles for the three selected schools, see section 4.2, indicated that each school had a different weekend power demand. The high school had a small demand; whereas the specialised and primary schools did not have any demand (excluding the sharp peak present in the specialised school profile). The one common factor between the schools was that there was a significant difference between the weekday power demand and the weekend power demand. Any data used to create typical/generic profiles must represent typical power demand of the school. The weekend power demand, similarly with the half days and abnormal profiles, do not represent a ‘typical’ working day’s power demand and hence have to be removed.

The resulting database, after all weekend power demand data was removed, was plotted (see Figure 94). The main difference between the full dataset (Figure 93) and the weekday dataset (Figure 94) is that the broad peak is more pronounced from 03:30-15:30. This further highlighted the requirement to remove any profiles deemed non-typical. Figure 94 also demonstrates that there are still several demand profiles that do not appear to resemble a broad peak, or the ‘typical’ profile shape.

The removal of the half days, electrically heated schools, weekend data and abnormal profiles was to ensure that non-typical power demand was removed from the datasets. The presence of abnormal profiles, and low unchanging power demand (that resembles primary school weekend power demand) indicated that there were schools present in the database that could be counted as abnormal power demand. It was essential for this data to be identified and removed from the datasets in order to create accurate ‘generic’ profiles that represented ‘typical’ school power demand.

The results from the initial analysis confirmed the importance of normalising the data by floor area, identifying the schools that used electric heating and factoring in school construction age. Another key outcome was the importance of categorising the schools into three different school types; high, primary and specialised high. The average profile analysis revealed that each type of school had a different profile shape, in terms of baseload, peak demand and duration of the broad peak. The weekday dataset, as shown in Figure 94 was subjected to categorisation incorporating the same three types of schools, see Figure 95.

One note of caution is that Figure 95 was only partially useful in identifying trends in power demand. The difficulty is that there are over 9,000 individual profiles to plot on one graph. The graphing software draws one school type category at a time resulting in a layering effect. In Figure 94 the specialised schools were drawn first, followed by the primary schools, and lastly by the high schools. This, results in the high schools appearing more closely grouped than the other schools. If the plotting order was reversed, then the specialised schools would look more closely grouped.

Although Figure 95 had a possible plotting issue it was still useful in providing a quick reference into how the different school categories impacted on the power demand.

7.1.2 Unwanted School Data Removal

Six schools were removed from the school database due to the associated power demand being identified as non-typical. Five out of the six removed schools were due to the schools having electric heating, as indicated by the profiles containing multiple sharp peaks. The remaining school, school 4, was removed due to it having abnormal power demand profiles.

School 4, (see Figure 96), was removed due the demand profiles exhibiting a varying (almost stepped) baseload and a sharp peak occurring during the day. The baseload appeared to start at $0.5\text{W}/\text{m}^2$ and had a congregation of profiles occurring at $1\text{W}/\text{m}^2$ step until $5.5\text{W}/\text{m}^2$. No other school within the database had this stepped

baseload that occurred both in the early morning and late in the evening. The profiles also appeared to drop to 0.5W.m^2 just before and after the broad peak (07:00 and from 18:00-21:30). When the data underwent seasonal analysis, it was discovered that the summer accounted for the lower morning/evening baseloads, winter accounted for the highest stepped baseloads, and both spring and autumn had the baseloads in-between. The seasonal analysis also revealed that the sharp peak, that occurs from 11:30 to 13:30, was also impacted by the seasons. The summer and autumn did not have a sharp peak, whereas this was apparent in spring and winter (with winter having the highest peak demand).

The seasonal analysis, as well as the general profile shape, suggested that this school had a combination of electric storage and electric space heating. In the early morning, the school uses electric storage heating from 00:00 (22:00 if counting the start of the cycle). The low demand in summer and high demand in winter highlighted that the heaters have to work harder in the winter due to the cooler temperature, and increased usage during the day.

The autumn and spring profiles demonstrated a mixed baseload and profile shape indicating that the heaters are used more intermittently, and due to the increased outdoor temperatures (in comparison to winter) are used less, and require less stored heat (hence less power demand). The broad peak in each profile had very little seasonal variation, suggesting this demand is related to lighting and IT, and the usage does not change throughout the year. The sharp peak being present in the spring and winter (and being a sharp peak) indicated that it was space heating related. The power demand of the school then drops down to the baseload value, before rising at 21:30 as a result of the electric storage heaters being switched on.

School 40, (see Figure 99), was also classified as having non-typical power demand profiles; however it appeared to have several similar traits to the other removed schools. The school has multiple sharp peaks occurring during the day and a large demand occurring in the late evening and lasting until 04:00. Seasonal analysis revealed that this demand was mainly associated with winter (with some profiles being associated with spring), and that the winter had the greatest sharp peak. The morning demand is due to space heating and not storage heating, due to the main demand only occurring in winter. Electric storage would be present throughout the year (as shown in the analysis of school 4's data). The cooler temperatures in winter could result in the space heating being used early in the morning to maintain a minimum temperature in the school building, perhaps even to stop water pipes from freezing. The multiple peak

demand was also impacted by the seasons, with winter having the highest demand, followed by spring. This further suggested that the school had electric space heating.

The other removed schools, schools 14, 17, 41 and 43, also had electric heating (see Figure 97, Figure 98 and Figure 101). Schools 14, and 43 had very similar profiles, with each having multiple sharp peaks occurring throughout the day, due to space heaters being switched on and off to maintain a preset temperature. Schools 17 and 41 are similar as both have sharp peaks only occurring in the early morning and late evening (also similar to school 4 in terms of time) and were associated with electric storage heating. Each school underwent seasonal analysis and seasonal differences (as expected) were observed, especially between the winter and summer. The difference between sharp peaks varied from 12-38W/m² between the schools.

The analysis of the removed school data highlighted the differences between the schools that used electric heating against the schools that used fossil fuel heating. The analysis also determined that the schools that were originally classified as non-typical, were actually electrically heated schools. When compared to each other, several similar traits were observed between the schools. The first trait was that the schools that had electric space heating had multiple sharp peaks that occurred throughout the day, and the schools with storage heating had a sharp peak (or demand) during the morning and late evening. The second trait was that the peak demand was broadly similar, with sharp peaks ranging from 60-90W/m² (however the demand of school 4 was considerably less).

The analysis of the removed schools, and what can be considered as the electric heated school database, demonstrated that the schools with electric heating can be compared and analysed together. The database could be expanded to determine if these broadly similar traits are extended across other electric heated schools. The analysis did however demonstrate that there is significant variation in the power demand profiles between each school (suggesting different heating systems and use). It is unknown whether or not this variability may hinder the creation of ‘generic’ profiles for schools with electric heating. Only the expansion of this separate database could answer this question.

7.2 School Category Datasets

School category is an important factor in the analysis of the school database. The results from the average profile analysis (section 4.2) and the categorised database (see Figure 95) indicated that each school type has different power requirements. To create

accurate ‘generic’ profiles of school demand, the school database had to be disaggregated into the different categories and analysed separately.

7.2.1 High Schools

The high school power demand profiles were represented by the red profiles in Figure 95). The data was removed from the schools database and analysed separately from the other schools, see (Figure 95). The previous analysis (sections 4.1.3 and 4.2) determined that the construction data of the schools was important to consider. Although there was not a strong link between energy demand and age of building, there were clear differences between older built schools and newer built schools.

The school descriptions table (see Table 5, see section 3.9.1) highlighted that there was a wide range of school construction dates, with the oldest being built in 1890 and the newest being built in 2009. The size of a school (by floor area) was an important factor to normalise to create a more accurate comparison. If it is assumed that newer built schools are more energy efficient, hence have lower power demands than older schools, then schools of a similar age have to be compared for an accurate analysis. This would result in either analysing the schools within a set time period (per decade) or determining a set point in time, and analysing the schools before and after it.

There are several new school build programs that have occurred throughout the UK, aiming at refurbishing or rebuilding old schools (Scottish Executive, (2011, Department of Education, (2000)). Hence two new age categories for the high schools were created, based on the dataset and the new school building programs. The categories were pre-2000 high schools and post-2000 high schools. This resulted in the post-2000 dataset having eleven schools, and the pre-2000 dataset having nineteen schools. Figure 102 demonstrates both the post-2000 data, shown by the red profiles, and the pre-2000 data shown by the blue profiles. One key output of plotting the two age categories together is that the newer high schools appear to be closely grouped than the older high schools.

To establish a better understanding of how the age of the schools influences the power demand, the two categories were analysed separately. The post-2000 schools have a baseload of 2-13W/m² and the peak demand varies from 15-25W/m². In comparison, the older schools have a baseload of 1-22W/m², and the peak also differs from the newer school, starting at 5W/m² and ending at 35W/m².

Figure 102 is useful in demonstrating the variability of power demand between the various high schools, as well as highlighting the variability within each age category

of school. The variability within the schools (and categories) can be due to several factors, including; construction material, equipment, how the building is used and whether any energy efficient measures are used. Also whether the school has a swimming pool or if open to the community, can have a large impact on the power demand profile. Schools with a swimming pool require extra power to drive heating pumps and AHU's to maintain a set temperature in the pool and pool room. After school use (at weekends or weekdays) will see a rise in classroom power demand as well as sport facility demand. The little variation between the new schools could be due to the schools being built to a similar design or using similar materials.

One outcome of the power profiles shown in Figure 102, is that it highlighted the different power requirements of new and old schools. It can be assumed that new schools are more energy efficient, and hence have lower power requirements than the older schools. If the peak and baseload demands of each age of school are compared, this assumption can be confirmed. The new schools have a maximum peak of $25\text{W}/\text{m}^2$ in comparison with the old schools that have a peak of $35\text{W}/\text{m}^2$. This indicates that the newer schools have a lower peak demand, and possibly indicates that they are more energy efficient. The baseloads can also be compared, with the old schools having a maximum baseload of $8\text{W}/\text{m}^2$ and the new schools having a maximum baseload of $9\text{W}/\text{m}^2$. Although the difference between the two ages of high school was only $1\text{W}/\text{m}^2$, it highlighted that the baseload of the new school was high, even though the peak demand was lower (in comparison to the old schools).

Another outcome of comparing the two categories of school profiles is the minimum peak demand. On the newer schools, this minimum peak is $15\text{W}/\text{m}^2$, and on the older high schools it is only $5\text{W}/\text{m}^2$. This would suggest that there are schools within the pre-2000 category that have a smaller power demand than the newer schools. A new school may have more small power equipment installed, including interactive smart boards, projectors, large computer facilities and air conditioning. Additionally newer schools may have increased lighting to meet newer lighting guides (Department for Education, (2011)). In comparison, older schools may only have basic IT equipment, with very few projectors or interactive boards. This could be due to limit space to install new equipment or outdated power systems that cannot cope with additional small power demands.

In order to examine the differences between the post-2000 high schools and the pre-2000 high schools, it was necessary to analyse each school type and age separately.

7.2.1.1 *Post-2000 High Schools*

The post-2000 high school weekday power demands demonstrated a similar demand pattern consisting of a single broad peak starting from 05:30-06:30 and finishing at 19:30 to 21:30. The schools demand profiles were closely grouped with baseload having a variance of $10\text{W}/\text{m}^2$ and peak having a variance of $12\text{W}/\text{m}^2$, the lowest variance of any other school category. There are several explanations for the post-2000 having broadly similar demand profiles. The first, is that schools in the post-2000 database were built within seven years of each other, suggesting similar construction standards and minimum equipment list. Several of the schools are based on the same design and contain the same facilities and equipment. This, almost standardisation of the newer high schools design could result in the schools having an almost identical power demand. Differences in the power demand will occur however, depending on how the school is used after-hours (during weekdays), and how the school is managed (in terms of energy/power).

The second explanation, is that the sample rate is too small or narrow to account for the variability within newer high schools. The eleven analysed schools may have been sampled from a certain category of high school, and hence may not represent the true modern high school stock. Expanding the post-2000 database may demonstrate considerable variation in power demand between the schools, or alternatively confirm that there is a limited difference in demand between the schools.

In Post-2000 high schools, there appeared to be little evidence of the expected rank order of seasonal power demand, as demonstrated by the limited variation between the seasonal profiles (in terms of shape, peak demand and baseload), see Figure 110 and Table 10. The small variation could be due to the schools varying their behaviour or energy policy very little regardless of outside conditions. Using lighting in summer, when not required, or heating in summer with windows left open are examples of these issues (as part of poor energy management, or energy management systems not being utilised properly). Other system use may not alter throughout the year such as small power systems.

Simple errors in a system set up can result in power wastage, and could account for little seasonal differences. It was also expected that the power demand associated with the AHU's would also be reduced in the summer time. The lack of change suggested that the AHU's are continually used throughout the year for ventilation needs, opposed to heating. With expansion of the post-2000 high school database, there could be a different seasonal impact than the one observed in the eleven selected schools.

7.2.1.2 Pre-2000 High Schools

The pre-2000 high schools represented a significant portion of the high school data (63%), was represented by the blue profiles in Figure 95. A clearer view of the pre-2000 high school profiles was found in Figure 104. The figure demonstrated that the demand profiles appeared to have a common broad peak from 03:00-22:00. The figure also highlighted that there was more variation in power demand profiles than the post-2000 high schools. The variation could be the result of the larger sample size in comparison to the post-2000 high schools, due to the wide range of construction dates (hence construction standards), and a wide range of applied energy efficient measures (lighting, double glazing, insulation).

The pre-2000 high schools underwent the same seasonal analysis as the post-2000 high schools (see Figure 105). The results indicated that there was a seasonal impact on the pre-2000 high schools (larger impact than the newer high schools).

The summer profiles had a limited variation within the baseload, as well as a small peak demand. There was additionally a large variation in peak demand of summer. The main grouping of profiles had a maximum/minimum peak demand of 8-14W/m², and the larger profiles varying from 22-39W/m². One significant difference was the proportion of winter and autumn profiles in comparison to the summer profiles.

The winter profiles had a larger baseload (9W/m²), when compared with the other seasons. The additional baseload could be the result of a climate linked system (heating or lighting), that is used constantly throughout winter. Several profiles had an initial rise in power demand occurring earlier than the majority of the summer profiles that could relate to the heating systems and lighting being switched on earlier in the other seasons. The winter profile also had a larger peak demand of 35W/m², although only 1W/m² more than spring. Lastly the winter profiles have a later fall in power demand than the other seasons and higher after school power demand. It appeared that the relative size of the active portion of the profiles, in terms of main power demand in hours, changed with the seasons. The active section of the demand profiles were associated with either user interaction, or automatic systems switching on/off equipment. Longer active sections, could be due to lighting being left on longer or heating systems being left on longer.

The active time could be established as the time from the initial rise in power demand from baseload, to the fall in power demand in baseload. The active times for spring, summer, autumn and winter were 16 hours, 16 hours, 16 hours and 17 hours. This indicates that the winter demand profiles had a longer demand period by one hour.

This further reinforces the possibility that certain systems were used for longer in winter, than in the other seasons.

The longer winter demand period, and the larger baseload and peak demand can be associated with how the power demand changes in winter. It has already been discussed that in winter, lighting usage is increased, in terms of both amount of lighting and duration of use. The larger after school demand, associated with school 20 also changed, through the seasons. This change was observed by investigating 15:30 to 21:30. Analysing this select time window highlighted that the after school power demand varies from season to season. This could be due to the indoor sporting facilities being used more due to the weather. The varying initial power demand rise time across the different seasons is most likely due to the energy management and heating systems compensating for the varying weather conditions. It will depend on how each individual school system has been setup, and whether there are changes to system active duration throughout the different months/seasons.

7.2.2 Primary Schools

The primary school database, once separated from the school database, consisted of eleven schools, however due to the removal of electric heated schools, this number was reduced to seven schools. The primary school power demand exhibited a broad peak occurring from 04:30 to 16:30-22:00, see Figure 106. The baseload ($1-10\text{W/m}^2$) was comparable to the baseloads of both the post-2000 and pre-2000 high schools. This suggested that the schools may have similar standby systems resulting in a similar power demand. The peak demand ($8-35\text{W/m}^2$) was comparable to the pre-2000 high schools, however the it could have been assumed that the peak demand of the primary schools would have been lower. This would be due to the primary schools having a lower intensity of small power than a high school, see Figure 65. The similarity of peak demands would in turn suggest that the primary schools have a similar power demand as a high school (i.e excessive due to a lower amount of small power and facilities), or that the high schools had a similar demand to the primary schools (i.e high schools appear more energy efficient). The former appears to be suitable.

One observation was that there was evidence of after school power demand, occurring from 19:00 to 22:00. The analysis of the sample primary school indicated that there was no after school power demand. It can also be assumed that primary schools are not used in the evenings and at weekends, unlike high schools (that do exhibit after school usage). Further investigation determined that the after school power

demand was related to only one primary school (school 34). It was discovered that school 34 was part of a larger campus, and shared facilities with a variety of other organisations, including a nursery, after school club (or out of school club) and a family centre. The shared facilities are fed from school 34's main power feed (where the power meter is located), resulting in after school power demand (although this demand is not actually related to the primary school).

The primary school data underwent seasonal analysis to determine whether the power demand of the schools was influenced by the changing seasons, see Figure 107. The results indicated that the primary schools had the greatest seasonal variation, with the difference between summer and winter being $7\text{W}/\text{m}^2$ (in contrast to post-2000 high schools being $2\text{W}/\text{m}^2$ and pre-2000 high schools being $5\text{W}/\text{m}^2$). The primary schools also conformed to the assumption that summer would have the lowest power demand, winter would have the largest, and spring/autumn would be in-between.

There are clear differences between the winter, autumn and spring profiles, as shown by the varying visibility of each colour of profile. The winter profiles appear to be the largest demand profiles. It can be seen that the baseload ranges from $3\text{W}/\text{m}^2$ to $10\text{W}/\text{m}^2$, and the main peak demand ranges from $9\text{W}/\text{m}^2$ to $35\text{W}/\text{m}^2$. The results also indicated that the winter profiles appeared to have a longer duration than the other seasons, as a result of increased use of lighting and heating.

Winter power demand also had the largest baseload, and could be the result of increased usage of external lighting, or the heating systems being placed in a standby mode to maintain a preset temperature. In contrast it appeared that the lowest demanding profiles were associated with the summer. The lower demand of summer will be the result of lighting and heating systems not being used as much, due to the increased outdoor temperature and global solar radiation. Additionally, there is little variance between the autumn and summer demand profiles in terms of shape, or baseload and peak demand. This suggested that the school use and occupant behaviour does not change during these months.

7.2.3 Specialised High Schools

The specialised schools represent approximately 10% of the entire school database (5 out of 48). With the removal of the electrically heated schools, this number was reduced to only four schools. This is a very small sample, and resulted in considerable variation in peak and baseload power demand, see Figure 108. The baseload and peak demand varied by $13\text{W}/\text{m}^2$ and $42.5\text{W}/\text{m}^2$ respectively, and

demonstrated that the specialised high schools had the largest variation in power demand of all the school categories. One common trait in the demand profiles, was the presence of a broad peak occurring from 05:30 to 17:30. The power demands also demonstrated limited after school usage, suggesting that the conclusions drawn from the average profile analyses may be applicable to the rest of the specialised database.

The seasonal analysis revealed several outcomes (see Figure 109). The first outcome was that the low power demand school (school 36) had minimal seasonal variation, with the peak demand for all seasons being approximately $10\text{W}/\text{m}^2$. Figure 109 indicated that the majority of the largest baseload profiles (of around $15\text{W}/\text{m}^2$) were associated with the summer season, and not winter as initially expected. The lowest baseload values are associated with winter and autumn. The results also indicate that there was variation within the summer profiles compared with the other seasons (excluding school 36).

There is also a clear divide within the winter profiles, with one grouping having a longer broad peak duration that is not apparent in the other seasons. The decrease in demand (from peak) occurs at 17:30 and at 18:30. When investigated, it was found that the second fall in demand was associated to one school (school 7). The other decrease in power demand was associated with schools 10 and 36. The specialised school analysis also demonstrated that in one school (school 7), the summer baseload was the largest, even over winter, unlike all the other schools both in this category and in the entire school database. It is unknown why the summer baseload demand is higher than the winter, however it does suggest that there is a seasonal dependant system used in the building (lighting or heating/AC).

The analysis of the specialised schools revealed that the power demand profiles were not congregated to the same extent as the other schools (due to a lack of data), and no firm conclusions could be drawn from the analysis. It was evident that there was significant variation of peak power demand (as well as baseload) within the schools, however the seasonal impact varied, with one school showing little impact.

7.2.4 Overall Analysis

The analysis of the school data, in terms of each schools 24 hour power demand profile further highlighted that each category of school has a different power demand, and hence had to be analysed separately. The resulting analysis on the separated databases revealed that there was a different variance in peak/baseloads within each category, as well as different seasonal impact between the school categories. The

analysis revealed that all school types, bar the post-2000 schools, were influenced by the seasons. This results in seasonal ‘generic’ profiles being required for all the school types bar the modern high schools, which will only need one set of ‘generic’ profiles (opposed to four).

The combination of each school category’s seasonal results, see Table 14, allowed a quick comparison of seasonal power demand between the school types. The result showed that the minimum baseloads for each season was almost identical for each type of school (with $1\text{W}/\text{m}^2$ variance in only 3 results). In terms of maximum baseload, post-2000 high schools had the largest demands, followed by specialised schools, pre-2000 high schools and primary schools. The larger baseload maximum in the newer high schools could be the result of increased small power intensity (with more systems being left on/standby out of school hours).

In terms of minimum peak demand, the post-200 high schools had the highest demand, followed by the specialised high schools, pre-2000 high schools and the primary schools. At this stage of the analysis, it appeared that the newer high schools had the highest power demand (due to it having the highest baseload minimum and maximum, as well as minimum peak). Similarly with the baseload, the newer high schools could have a higher use of small power (more interactive white boards, projectors, general IT), as well as increased use of air conditioning. This could result in a higher minimum peak demand in comparison to the other school types. Lastly, in terms of the maximum peak demand, the results indicated that specialised high schools had the highest demand, followed by post-2000 high schools, primary schools and pre-2000 high schools. It was already discovered that the specialised high schools had larger total annual energy consumption than the other schools, hence it was expected that they would have the highest maximum peak demand.

The results showed that the newer high schools appeared to have a higher power demand (excluding the maximum peak demand) than the other high schools, and that primary schools had the lowest power demand. Only when the maximum peak demands were introduced did the newer high schools have the lowest demand. The results were useful in demonstrating that the newer schools, in some circumstances, were not as energy efficient as they might assumed to be. However, the post-2000 high school maximum peak demands were lower indicating that the newer schools do outperform the other school types in the right conditions. The lower peak demand should in turn result in lower total annual energy consumption in comparison to the other schools.

7.3 ‘Generic’ Profiles and Benchmarks

The previous analysis sections provided a basic foundation for creating ‘generic’ or typical profiles. The analysis revealed that in order to create ‘generic’ school demand profiles, key factors had to be considered. These factors included construction age, school type, heating type and seasonal influence. Applying these factors to the schools database resulted in five separate school databases; a) electrically heated schools, b) post-2000 high, c) pre-2000 high, d) primary schools and e) specialised high schools. A percentile analysis was applied to each database (excluding electrically heated schools), and four sets of outputs were created. The output files consisted of five percentiles per season per school. The percentile profiles for each school are shown in Figure 110, Figure 112, Figure 113, and Figure 115.

The power demand profiles can also be used to indicate the possible effects of introducing renewable technology or new energy management systems have on a buildings power demand. The predicted power produced by wind turbines or solar panels could be added/subtracted from the ‘generic’ profiles, providing an indication of the potential impact on the baseload or peak demand of the building.

With the establishment of a model that derives generic power demand profiles (based on inputted building data) it is possible to determine the impact of changing building systems (to newer/energy efficient replacements). An example would be anticipating the effect of replacing equipment with renewable technology, and determine the maximum benefits. Similarly, if the breakeven point was established, the extent to which renewable energy would have to replace gas based systems to reach this breakeven point could also be established.

The percentile analysis was designed to create five ‘generic’ demand profiles for each dataset. The 10th, 25th, 50th, 75th and 90th percentiles were labelled ‘Excellent’, ‘Good’, ‘Typical’, ‘Bad’ and ‘Very Bad’. The extra ratings were to provide further detail on the power demand of each school. The percentile analysis was applied to each high school dataset, and key points (baseload, peak demand and daily energy consumption) were recorded.

A further development of the ‘generic’ demand profiles would be to create generic power demand profiles for electrically heated schools. The identified electrically heated schools had considerable peak power demand, as well as considerable energy consumption in comparison to the fossil fuel heated schools. The removed school data from, schools 4, 14, 17, 40, 41 and 43, had moderately unique

power demand profile, and were dependant on whether the school had electric storage, electric space heating, or a combination of both.

In order to analyse the schools, and hence create ‘generic’ profiles, the schools would need to be sub-divided into these different electrical heating categories. However due to the variability of each profiles, it is unknown whether or not the power demand from electrically heated schools could be generalised.

7.3.1 Post-2000 High Schools

The post-2000 underwent percentile analysis to produce five ‘generic’ profiles, see Figure 110. It was established that there was almost no seasonal variation in the modern high schools. As a result it was not necessary to create separate ‘generic’ seasonal datasets. The resulting demand profiles hence represented all four seasons.

The power demand profiles all exhibited a broad peak, and all had a generally similar time for the initial rise in power demand (02:30). One key characteristic of the power demand profiles was that there was an almost fixed variation of approximately 1.5W/m^2 between the peak demands. This fixed (and low) peak variation is related to the number of schools, and the similar power demand of each school within the post-2000 high school database. The power demand profiles for each school, as shown in Figure 103, demonstrated that there was not significant variation between the each of the schools. The analysis of the power demand profiles shown in Figure 95 revealed that the post-2000 high schools had the smallest peak variation in comparison to the other types of school.

The baseload power demand had a marginally greater variation ($1\text{-}2\text{W/m}^2$) and is a result of there being a larger variance in baseload power demand in the different schools, see Table 15. The 50th, 75th and 90th percentiles all demonstrated an after school power demand, although it was more apparent in the 90th percentile profiles, from 17:30 to 21:30. Not all the schools in the post-2000 high school database had after school power demand, and this is reflected in the 10th and 25th percentile profiles. The impact of the after school power demand (or the amount of power demanded) also varied, with the 90th percentile profile having the largest demand and the 50th having a small amount of demand. This reflected on both the schools in the database and the percentile analysis methodology.

A further improvement on the post-2000 high schools would be to either separate the schools that have after school power demand (from those that do not), or create a filter to remove any after school power demand. This would enable either a

separate ‘generic’ profile for schools with after school power demand, or create a ‘generic’ after school power demand. The latter could be included in a more developed power demand model. The user could check whether the school has after school power demand, and enter the other key school details (age, floor size, type, etc) and a ‘generic’ power demand profile representing a school with after school power demand could be generated.

The ‘generic’ power demand profiles established that as the baseload increased, the peak demand increased (as shown by Figure 110 and Table 15). To determine if this link was applicable across the actual post-2000 high school database, each schools average peak and baseload demands were plotted, see Figure 111. The results highlighted that a large baseload does not result in a large peak demand. School 25 had the highest peak demand ($20\text{W}/\text{m}^2$), but did not have the highest baseload. Instead, school 18 had the largest baseload, with a value of $6.7\text{W}/\text{m}^2$. Conversely, the school with the smallest baseload, school 46, had a moderately high peak demand. The link between the peak demand and baseload is a result of the percentile analysis methodology.

7.3.2 Pre-2000 High Schools

The ‘generic’ power demand profiles generated to represent the pre-2000 high schools followed the expected seasonal rank order of; winter, autumn/spring and summer (from highest to lowest demand). The percentile demand profiles exhibited a similar shape across the seasons, and demonstrate a similar variation between the peak demands and baseloads, with the exception of winter, that has slightly larger variation between percentiles. The difference between the peak demand of the 10th and 90th percentile was approximately $15\text{W}/\text{m}^2$ across the seasons, which was considerably higher than the post-2000 schools ($6\text{W}/\text{m}^2$).

The variation between the 10th and 90th percentile profiles was due to the large variation in peak demand of each school, see Figure 110. The pre-2000 high school database, the range of construction dates, and different degrees of retrofitting that the schools had dissimilar power demand patters, as highlighted when Figure 103 and Figure 104 are compared.

The pre-2000 generic demand profiles exhibited after school power demand in all the ‘generic’ power demand profiles (as identified in the 50th, 75th and 90th post-2000 high school profiles). The after school power demand appeared more pronounced than the post-2000 high schools, and was due to both the pre-2000 high school containing a

greater number of schools, and a greater number of school that had an after school power demand. A similar after school power demand separation/filter could be applied to the pre-2000 school data (as discussed in section 7.3.1). The ‘generic’ profiles all had after school power demand that would not represent a school that only operated during the school hours (i.e. no after school demand). In this case, a separate set of generic profiles, or a system to add/remove after school power demand would be beneficial.

Lastly, there was evidence of an early power demand rise in both the 75th and 90th demand profiles, occurring from 04:30 to 06:30. This early power demand is apparent in all four seasons, however it is more pronounced in the winter profiles. Further investigation revealed that the demand was related to school 44, and was not present in any other pre-2000 high school. It was unknown why this school had this demand, however due to time this demand occurred at, it was most likely due to heating systems (AHUs) switching on to heat the school before the pupils/staff arrive.

7.3.3 Primary Schools

Twenty ‘generic’ profiles generated for the primary schools represented the five percentile profiles for each of the four seasons. The results demonstrated that generally the rank order of seasons were winter, autumn, spring and summer (highest to lowest), based on peak power demand. The baseloads also appeared to be broadly similar across the seasons, with the winter having the greatest baseload demand and variation between the percentiles. The larger baseload demand in winter is the result of systems being used (such as external lighting), and the larger peak demand in winter is the result of lighting and heating systems being used more and for longer.

The variance that exists between the profiles, as shown by the baseloads and peak demand, was due to the small number of schools that were present in the primary school database (especially after three electrically heated schools were removed). Similarly with the previous sections, expanding the database could reduce the variation between the profiles.

The ‘generic’ profiles exhibited a broad peak that is present in the other schools, and as identified as ‘typical’ power demand. One difference between the high school demand profiles and the primary school demand profiles was the lack of after school power demand. The average primary school power demand analysis (section 4.2) demonstrated that the primary schools had a sharp decrease in power demand (from peak to baseload). This quick drop in power demand and lack of after school power

demand can be found in all the ‘generic’ profiles, bar the 90th. The 90th percentile profiles in each season appeared to have power demand from 18:30-21:30 that resembled after school power demand (as found in the high school profiles). This demand being present in only the 90th percentiles could suggest that it relates to only one of the schools, and in turn does not represent the entire primary school database. An early morning power demand (01:00-04:00) was also present in the 75th and 90th winter power demand profiles. This could also be the result of only one school (school 34), due to the demand being present in only two profiles.

The baseload was constructed as a result of certain equipment that is never turned off, or has a fixed power demand. Although there could be equipment present that transitions from baseload/standby into active power usage resulting a relative decrease in baseload demands. In all the seasons except summer, it appeared that the standby in the morning (before the rise in power demand) was higher than the baseload after the initial power demand fell. This effect is more obvious in the 75th and 90th percentiles, in the three months (spring, autumn and winter). It is unclear why the changing baseload occurred. It should be noted that the percentile profiles were created by analysing the entire primary school dataset (excluding school 14 and 41).

A further analysis of the ‘generic’ profile data was carried out to determine what the main driver of daily energy consumption was; either baseload or peak demand. The ‘generic’ analysis indicated that both factors appeared important at influencing the daily energy consumption. To determine the primary influencing factor, the ‘generic’ daily energy consumption was plotted against both peak and baseload demands. The results, see Figure 114, revealed that the peak demand had the strongest relationship (with a R² value of 0.95), with the baseload having an almost equal relationship (with an R² value of 0.93). This could be due to the energy consumption leading up to the peak demand, and the subsequent fall from the peak demand, being greater than the total baseload consumption. It was apparent that both factors were important to consider when regarding total energy consumption.

7.3.4 Specialised High Schools

The specialised schools represented the smallest school dataset, and as a result had the greatest variation between the percentile power demand profiles (in terms of peak demand and baseload). The variation was more apparent in the spring and autumn profiles, between the first grouping of profiles (10th, 25th and 50th) and the second group (75th and 90th), in terms of peak power demand. The variance between the peak

demands of the 50th and 75th, and 90th was 17.8W/m² and 26W/m² for spring respectively. The variance was due to the small number of schools in the database, as highlighted in Figure 108. The figure demonstrated that there were large separation distances between each school demand and as a result, each individual school's power demand was identifiable. Increasing the size of this database would reduce this variance, and provided more meaningful and more statically valid generic profiles representing the specialised schools.

The large variance in peak demand (and baseload) was also present in the summer and winter profiles. The winter generic profiles had greater peak demands, especially the 50th percentile power demand. Although the variation between the 50th and 75th/90th profiles was reduced (in comparison to the spring and autumn profiles), the variation between the profile baseloads increased. This increased baseload variation (and smaller peak demand variation) was also apparent in the summer 'generic' profiles, with the summer 90th percentile profile having the highest baseload. The variation in both summer and winter 'generic' profiles relates to the small number of schools in the database. The variation in the baseloads was due to each specialised high school having a different baseload demand (see Figure 115). The high 90th baseload demand was related to school 7. The high baseload demand could be due to the school using the heating (in terms of heating pumps) constantly to maintain a comfortable temperature in the school before the school pupils arrive.

The specialised high school demand profiles partially follow the expected seasonal rank order of summer having the lowest power demand, winter having the highest power demand, and spring and autumn having a power demand in-between summer and winter. This rank order is correct after the 50th percentile profiles (in terms of peak demand). The summer peak demand in the 10th and 50th profiles was larger than the other seasons. The summer peak demand was smaller than the winter peak demand in the 50th percentile profile, however was still almost double the peak demands of autumn and spring peak demands. Only in the 75th percentile profiles was the expected rank order achieved.

The unexpected rank order in the 10th, 25th and to a lesser extent in the 50th percentile profiles was related to school 21. The high demand in summer in comparison to winter suggested that the school contained air conditioning. The extended use of air conditioning in summer could account for the higher peak demand of the 10th and 25th percentile power demand profiles.

7.3.5 Comparison Between Categories

The comparison between the spring 50th percentiles for each category of school was to highlight the differences in how each school type demands power, see Figure 116. The 50th percentile profiles were chosen (instead of the other percentile profiles), because they represented the median power demand for each school category. The results indicated that the specialised schools had the lowest peak power demand, followed by the pre-2000 high schools, and followed by the primary school, and lastly the post-2000 high schools. This result was not as expected, as the previous analysis sections (average profile, all profiles, generic) indicated that the specialised high schools would have the highest peak power demand, followed by the primary schools, followed by the pre-2000 high schools, and lastly the post-2000 high schools. This is true when the 75th and 90th percentiles are analysed, however the 10th, 25th and 50th exhibit the reverse of this rank order.

The reason for this unexpected rank order was due to the separate school databases, and in turn the number of schools in each database. For example, comparing the school demand profiles for the post-2000 high schools (Figure 103) and the pre-2000 high schools (Figure 104), demonstrates the range in peak demand between the two school types. The pre-2000 had more school demand profiles with peak demands ranging from 7-23W/m², whereas the post-2000 high schools had a similar peak power demand from 13-24W/m². This resulted in the median peak demand for the older high schools to be approximately 15W/m², and 18.5W/m² for the modern schools. This is repeated across the other time periods (00:00, 00:30, etc).

The baseload has a moderate variation (in comparison to the peak demand), due to each school category having a similar baseload, and similar variation between the baseload values. This was also applicable of the initial rise in power demand, and accounts for the initial rises being closely grouped. This difference in the median values was also apparent in the other school types. When the specialised high school ‘generic’ power demand patterns are viewed, see Figure 115, the variation that existed between the 50th and 75th percentiles (in spring and summer) was considerable. This suggested that the school database was too small, and that another seasons may have been a better comparison between the school types.

This comparison could be applied to the other seasonal 50th percentile profiles, to determine how the power demand in each school type varies, and how the rank order is affected. Additionally, the two extremes of the percentile analysis, the 10th and 90th

percentile profiles could undergo the same analysis, to further highlight the differences between school types and seasons.

7.3.6 ‘Generic’ Benchmarks

The daily electrical energy consumption for each percentile, season and category were calculated in order to provide a consumption figure that could be used in conjunction with the power demand profiles. It was deemed more suitable to create annual energy (electricity only) benchmark data that could subsequently be used in a similar way as current published benchmarks. The key advantages of the ‘generic’ benchmarks over the current published benchmarks are that there are additional schools categories, and additional benchmarks for each season. These advantages improve on several of the previously stated issues with current energy performance benchmarks including school coverage (how representable are the benchmarks) and what the possible seasonal impact on the energy consumption.

The created benchmarks do suffer from the same data issues as the power demand profiles, due to the benchmarks being created from the percentile power demand profile data. The main issue, is how valid the benchmarks are when they were calculated on a small dataset; primarily regarding the specialised and primary school datasets. To overcome this data issue, each school database should be increased to a larger number of schools, with a wider range of building details.

The annual energy (electrical) consumption benchmarks shown in Table 11 were designed to represent the seasonal energy consumption for each school type (and percentile). The benchmarks were created using the seasonal ‘generic’ power demand profiles for both the weekday and weekend data. The daily energy consumption for both the weekday and weekend data was extrapolated to account for the 261 weekdays and 104 weekend days in a year. However, this approach failed to account for school holidays and assumed that all weekdays (regardless of holidays) were the same. For the majority of the analysis undertaken in the previous results sections, the school database had to be adjusted to remove the school holiday data. This was due to the considerable power demand difference between holidays and non-holidays.

From analysing the holiday data, the holiday power demand data was similar to the weekend power demand. Primary and secondary schools demonstrated marginal holiday power demand, the majority of demand resembling an unchanging baseload (due to the schools not being used). The high schools, conversely, had power demand during the holidays, due to the schools being used by the communities (appropriate to

the community schools), and by summer clubs. This was also similar to the high school weekend power demand. The benchmark data sets were adjusted to account for the holiday power demand using 190 weekdays and 175 weekend days (the weekend days including weekend days and holidays).

There were two inherent issues with this approach; a) the assumed energy consumption, and b) the number of holidays. The assumed energy consumption of the holidays may not equal the consumption of the weekends. Although the holiday analysis demonstrated that the power demand was similar to the weekend demand. There may be holidays (or weeks) that have no power demand (from baseload), due to the school being completely closed to the public. This is more applicable to the high schools opposed the specialised/primary schools due to the presence of after school power demand.

The second issue arose when selecting the number of school holidays and when those holidays occur. The number of holidays and the times of those holidays can vary between each local authority. The number of school holidays in Scotland appeared to be the same; however the number of holidays in each month varied considerably. The varying number of holiday days in each month would impact on the seasonal energy consumption. To overcome this issue, the local authority of each school was marked, and the majority of schools from the same authority identified. The school holiday dates for this local authority was selected and applied to the ‘generic’ dataset. The holiday dates represented the majority of the data, hence was deemed an appropriate selection.

Two benchmark tables were created; seasonal benchmarks (see Table 19) and annual benchmarks (see Table 20). The annual benchmarks were a simple summation of the seasonal benchmarks, and were created as a comparison to the published energy benchmarks. A direct comparison between the published benchmarks and the ‘generic’ benchmarks was not straightforward, due to the published benchmarks being rated as ‘Good’, ‘Typical’ and ‘Bad’, where as the ‘generic’ benchmarks were organised into ‘Excellent’, ‘Good’, ‘Typical’, ‘Bad’ and ‘Very Bad’. The ‘typical’ rating in both benchmark datasets represented the median and hence, was comparable.

The published ‘typical’ primary school benchmarks ranged from 34-65kWh/m²/yr, and the ‘generic’ benchmarks was 50.87kWh/m²/yr. The ‘generic’ benchmark does lie within this range, however is closer to the upper range. The small sample of primary schools studied may result in a high annual benchmark figure when compared with other studies. The published ‘typical’ high school benchmarks ranged

from 27-39kWh/m², and in comparison the post-2000, pre-2000 and specialised schools had ‘generic’ typical benchmarks of 64.9kWh/m², 50.8kWh/m² and 51.36kWh/m².

The typical ‘generic’ benchmarks for the three categories of high school were not within the published ‘typical’ benchmark limits. Referencing the benchmark and annual energy consumption comparison (see Figure 68 and Figure 69) demonstrated that the published benchmarks did not represent the collected dataset. The ‘generic’ benchmarks, in contrast, represented the collected database. If the collected database was expanded to include a larger number of schools, the generated ‘generic’ benchmarks could change as a reflection on the new database.

The ‘generic’ benchmarks, (Table 19 and Table 20), demonstrated that the rank order for the 10th and 25th percentiles was the specialised high schools having the smallest annual energy consumption, followed by the pre-2000 high schools, followed by the primary schools, and lastly the post-2000 high schools having the largest annual energy consumption. In the 50th percentile, the rank order remained the same, bar the pre-2000 high school having the lowest benchmark, swapping with the specialist high schools. the rank order of the schools changed in the 75th percentile, the pre-2000 high schools having the lowest benchmark, followed by the primary school, followed by the post-2000 high school, and lastly by the specialised high schools.

Finally in the 90th percentile benchmarks, the post-2000 high schools had the lowest benchmark, followed by the pre-2000 high schools, followed by the primary schools, and lastly by the specialised high schools. The changing rank order of schools between the different percentiles reflects on the difference in power demand (in terms of peak, baseload and duration of demand) between each school.

The differences in the calculated ‘generic’ benchmarks between the school types, percentiles and seasons, reinforces the concept of having more detailed energy performance benchmarks. The produced ‘generic’ energy benchmarks found in Table 19 and Table 20 helped address the previously stated issues with benchmarks by introducing school categories, and introducing seasonal impact.

7.4 Validation of the Collected Data

There is one potential issue with the conclusions drawn from the collected school and office databases. This issue relates to how valid the gained results/conclusions are, when applied to the wider non-domestic building stock. The small number of schools in the separate school electric power databases, especially the primary and specialised high schools, may result in low confidence in the generic power profiles. The small number

of schools resulted in large variations between the peak demand and baseload values. As result of the ‘generic’ power demand profiles and ‘generic’ benchmarks being constructed using the same school database, they are also susceptible to this validity issue.

This issue is also applicable to the thermal analysis. The similar traits (baseload, peak/broad peak) were identifiable in only four (out of five schools). A sample of only five schools could not represent the entire school building stock, especially when factors like category, construction age, use and whether the school has a swimming pool, are unaccounted for.

By expanding the database to include more schools (within in each category), the generic demand profiles could represent not only the studied schools, but the wider school building stock.

Chapter 8 CONCLUSION

This research project focused on addressing four research questions, the questions were;

1. *If energy data is analysed at a finer time resolution does this approach provide a clearer insight into how buildings consume energy?*
2. *Can the power demand of non-domestic buildings be generalised, and hence 'generic' power demand profiles representing typical power demand be generated?*
3. *Using the 'generic' power demand profiles, can 'generic' energy performance benchmarks be generated?*
4. *By extension, can 'generic' power demand profiles and performance benchmarks be generated for thermal demand, and for other types of buildings?*

8.1 Data Time Resolution

A key finding of this research is that the current energy performance benchmarks have limitations as predictors of energy consumption or power demand as they are generally based on annual consumption. The advantage of benchmarks is that they can be used as a comparative or predictive tool, providing a quick insight into how a building consumes energy. However, it is also important to establish how representative the published energy performance benchmarks are to the wider non-domestic building stock. One finding of this research is that there appears to be major limitations of using current benchmarks as several factors have to be taken into consideration if benchmarks are to improve the predictive value in defining how buildings consume energy. Examples of the influencing factors identified in this research include; floor area, how the building is used (in terms of category), construction age, heating type and outside weather conditions (or season). Additionally annual energy consumption figures lack detail of where and when energy is used in a building. This research suggests that the extent of the impact of these factors on total energy consumption, as well as the power demand, cannot be ignored and must be accounted for, by any future benchmarks if improvements in future predictability is to occur.

Floor area, as defined from school power data, appears to be an extremely important factor in defining building energy consumption, with larger buildings

consuming more energy than smaller buildings. In addition, the age of the building appears to have a relationship with energy consumption, although this relationship did not appear to be linear in nature.

The comparison of the annual energy consumption of the schools in this research against the published energy performance benchmarks highlighted the importance of categorising the schools (high, primary and specialised) and determining the heating type (electric or fossil) of the individual school. The comparison of the published benchmarks derived from this research, suggest that caution must be used when the published benchmarks are used to define a building's energy consumption.

Establishing that heating type, floor area and school category are therefore important factors in the analysis of school energy demand and it is therefore important to normalise the data by floor area and the type of school. Pronounced differences were observed in total annual energy consumption between the three school types. A key part of this research was to determine if finer time resolution offered advantages over annual energy performance benchmarks as a predictor of a building's energy consumption.

One school was selected from each of the three school categories, and average weekday and weekend daily half hourly power demand profiles were created, as well as average daily seasonal power demand profiles. The weekday and weekend profiles were compared to highlight the difference in power demand between each school.

The results revealed that the weekend power demand was considerably lower than the weekday demand, and that the demand varied between the school types. The high schools had the highest weekend demand, whereas the primary and specialised schools had only a baseload demand, due to the school not being open at the weekend. The weekday profile analysis showed the differences in peak demand, baseload and duration of the broad peak between the schools. The specialised schools had the highest peak demand, followed by the primary schools, and lastly the high schools. The weekday analysis also highlighted that only the high schools had an after school power demand (generally from 17:30-21:30), whereas no after school demand was present in the primary school or the specialised school. Thus, these findings suggested that finer time resolution identifies differences in power demand that relate to periods of occupation. This subtlety is lost if only an annual energy performance benchmark was used to predict the schools energy consumption.

Another advantage of using a more refined method to generate benchmarks to estimate energy consumption is that other factors can be included. Clearly, the seasons

have a pronounced effect on a building's energy consumption. At the outset of this research, it was assumed that winter would have a higher power demand (hence energy consumption) than summer. The results revealed that there was significant seasonal variation in the high school and specialised high school, but only marginal variation in the primary schools. As anticipated the power demand was greater in winter than summer. This reinforced the requirement for analysing schools by the different category and taking seasonal variation into account. Interestingly, the seasons had a different effect on the office building's power demand. Office 1 conformed to the expected seasonal impact of winter having a higher demand and summer having a lower power demand. However office 2 demonstrated a reverse of this expectation, with summer having the higher power demand. This was a result of office 2 using air conditioning (or a form of AC) opposed to mechanical ventilation (as found in office 1). Thus in addition to having to take the seasons into account, care must be also taken to determine what heating and cooling systems are included within a building as each of these variables can have a major impact on the building's power demand. Again, the impact of these factors would not be identified if only annual benchmark values were used to predict the buildings energy consumption.

The seasons appeared to have mixed impact on the power demand for the offices, with one office having high power demand in winter and the other having higher power demand in summer. The assumption was made that this would be related to local weather, in terms of outdoor temperature and global solar radiation. The results of the half hourly power demand for both offices demonstrated that there was not a significant link between the power demand and outdoor temperature/global solar radiation. This suggests that there are other weather variables that either solely or collectively contributed to the seasonal impact on power demand on these two offices.

This research, based on the analysis of half hourly power demand profiles, demonstrated differences between the various school types and seasonal influence (in terms of peak, baseload and duration) on power demand. The next stage was to define what systems within the buildings contributed to the changes in power demand. The assumption was made that systems such as heating, lighting and IT equipment would contribute to the changes in power demand. In order to confirm this hypothesis more detailed power data (in the form of school distribution board data) was analysed. The advantage of analysing distribution board data was that the power demand of each main school system was known. Overall, the results confirm the hypothesis with largest demand being associated with AHU's (associated with the heating) and lighting/power

sockets. In contrast IT appeared to have minimal contribution to overall power demand. This additional detail into how and when power is demanded would be lacking if benchmarks based on annual consumption were used to predict the buildings energy consumption (or power demand).

The initial analysis of the electricity data demonstrated that floor size, construction age, building type (office/schools), building sub-category (primary school, high school), seasonal impact and heating type had varying (but still important) impact on building power demand, and hence energy consumption. These factors as they have a pronounced impact on power demand should be included in future benchmarks, if a more reliable comparison is to be made on how buildings consume energy or to predict future consumption. Finally, the use of more detailed power demand data (or energy data) collected over smaller intervals (i.e. half hourly over annual) improved the predictability of subsequent benchmarks.

This research has demonstrated that finer time resolution in the collection of energy/power data gives a clearer insight into how buildings consume energy. The next part of the research was to determine if power demand of a non-domestic building could be generalised and if so, could 'generic' power demand profiles be developed.

8.2 Generic Power Demand Profiles

This research has demonstrated that 'generic' power demand profiles offer a solution to overcome several of the identified issues associated with current energy performance benchmarks. This was established by analysing energy consumption data at a finer time resolution (half hourly data), such that a more detailed understanding of energy consumption (and power demand) could be gained. Generic power demand profiles (at a half hourly time resolution) appear to offer an alternative to energy performance benchmarks by providing a more detailed view of power demand. The advantage of this approach was that key features of power demand (peak demand, baseload, duration of demand) can be analysed to determine their contribution to total demand profiles. Additionally, once the key influencing factors of power demand (or energy consumption) have been identified, then their subsequent impact can be observed in power demand profiles.

Analysis of the individual power demand profiles for each school suggested a common broad peak and this was considered to be a 'typical' power demand in each school. Therefore, it appeared in this situation a generalised view of power demand in schools could be defined.

The 'generic' power demand profile was further refined by introducing the variables discussed previously (category of school, construction age, and season). Each variable had its own effect on the power demand profile. Generally, each variable were not mutually exclusive, but had a relationship to each other. Each category of school had its own 'generic' profile, and when age of school was taken into consideration, additional 'generic' profiles were generated as a result of this variable. For example the initial generic profile for a high school generated two sets of generic profiles for pre-2000 and post-2000 high schools. Similarly, the same situation was observed for the impact of seasons on 'generic' profiles. Each season (spring, summer, autumn and winter) generated its own individual 'generic' profile dataset.

The results from this research suggest that 'generic' profiles can be generated and that the impact of factors, such as season, category and age of schools can be accounted for with subsequent generation of 'generic' profiles that take these factors into consideration. However, a potential issue with this conclusion, is related to how statistically valid the generated 'generic' profiles are. The small number of schools in the respective school type databases, especially the primary and specialised high schools, may result in a low confidence being placed on any 'generic' power profile. This can only be answered by expanding the database to include more schools in each category and compare the resulting generic profile against the profiles generated in this research project.

The conclusion is made that 'generic' power demand profiles can be generated. The next part of this research was to derive energy performance benchmarks based on the 'generic' profile data.

8.3 Generic Energy Performance Benchmarks

In order to compare current published benchmarks, it was necessary to convert daily generic energy consumption (in Wh/m²) to annual energy consumption (kWh/m²). A comparison of the generic energy performance benchmarks, created from this research project, highlights the limitations associated with current energy performance benchmarks. Overall, benchmarks generated from this research appeared to have higher annual energy consumption (per floor area) than the published energy benchmarks. The published 'typical' high school benchmarks ranged from 27-39kWh/m², and in comparison the post-2000, pre-2000 and specialised schools had 'generic typical' benchmarks of 64.9kWh/m², 50.8kWh/m² and 51.36kWh/m². However, in the case of

the primary schools, the 'generic' energy benchmarks fell between the upper and lower limits of the published benchmarks.

The most likely explanation for the higher (and lower for primary schools) annual energy consumption observed with the generated generic energy benchmarks in this research is that they include the factors of construction age, category of school and seasonal impact, which are 'marginalised' in the current published benchmarks.

A potential weakness of the 'generic' energy benchmarks generated in this research, relates to the fact that they have been generated from the 'generic' power demand profile data. Thus, the 'generic' energy benchmarks have the same inherent weakness as the 'generic' demand profiles. Only by generating 'generic' energy benchmarks from a larger sample size and comparing the subsequent benchmarks against those generated in this research will their validity be confirmed.

On the assumptions that the methodology for generating 'generic' power demand profiles has wider application, the methodology was applied to both thermal and office data.

8.4 Thermal Demand

The finding of this research is that the profiles for thermal demand are different from power demand profiles. This is an important observation as it also highlights an apparent weakness of the current energy performance benchmarks. One significant weakness is that current energy performance benchmarks relate to either total energy consumption (thermal and power), or are solely based on electrical energy consumption. Therefore, establishing thermal 'generic' demand profiles and hence 'generic' thermal benchmarks will provide additional information on a building's energy consumption rather than simply relying on current benchmarks.

Although the research project set out to develop 'generic' profiles for thermal demand, the limitations of available thermal demand data has placed limitations on interpreting thermal demand data and hence, made it impossible to generate a generic thermal demand profile. However, it was possible to identify potential key traits that would be consistent with a typical demand profile. Additional thermal data would be required to confirm if these traits could be considered 'generic' and sufficient to generate a thermal 'generic' demand profile, and hence a generic energy benchmark.

By incorporating 'generic' thermal demand profiles into generic power demand profiles, a combined 'generic' energy demand profile can be constructed. With the

construction of the 'generic' energy demand profiles, 'generic' energy consumption benchmarks (that relate to both thermal and power) could hence be created.

In addition to determining if it was possible to develop 'generic' thermal demand profiles, the appropriateness of the methodology on other non-domestic buildings was studied. Data from two offices were used in the analysis.

8.5 Other Building Types and Heating Type

Unfortunately there was insufficient office data to determine if the power demand profiles of the two offices were similar (or differ) to the different school power demand profiles that were previously analysed. Even within the office data, two different power demand profiles were observed. Interestingly, the power demand profiles showed different seasonal impact, one with a higher power demand in winter, and the other with a higher demand in summer. This suggests that it is important to establish the nature of heating and cooling within a building. Thus it is important to establish in which category the office falls (a third option is possible i.e. the office has air conditioning and heating) with respect to heating and air conditioning (or mechanical ventilation). A simple 'generic' power demand profile may not be possible for offices. It may be necessary to create several 'generic' power demand profiles to take into account heating and cooling.

Finally, the application of generating 'generic' power demand profiles (and benchmarks) to electrically heated schools was briefly studied.

Again, unfortunately, there was insufficient data to allow a conclusion to be drawn. Several traits were identified that would merit further investigation with a larger database. These traits included; a broad peak, sharp peak(s) and occurrence of each peak. Further research will confirm if these traits do in fact represent a generalised demand profile and will provide the means to generate 'generic' demand profiles.

8.6 Overall Conclusion

The findings in this research suggest that the current energy performance benchmarks have limitations as a predictor or as comparator of energy consumption. These limitations can be overcome by using the derived 'generic' power demand profiles and 'generic' energy benchmarks identified in this research.

Generic energy performance benchmarks generated from the generic power demand profiles appear to provide a more robust indicator of 'typical' energy consumption and power demand of non-domestic buildings. However, only with their wide spread application to various non-domestic building types, further comparison

against published energy performance benchmarks, will the question of how representative they are to the non-domestic buildings stock, be answered.

8.7 Research Originality

To determine the appropriateness of current energy performance benchmarks in predicting building energy consumption. This involved a) the identification of factors that influenced energy consumption and power demand, b) the generation of ‘generic’ power demand profiles and ‘generic’ energy performance benchmarks and c) comparing the derived benchmarks against the current benchmarks.

8.8 Recommendations

There are several recommendations if the research outlined in this thesis was continued or developed. The first recommendation is that the collected school energy databases (school electricity and school gas,) are expanded to include a greater number of schools of each category. The expansion should result in a more equal comparison between the different categories of school, as well as the other influencing factors (construction age, heating type and presence of a swimming pool). This increase in number of analysed schools would confirm how representative the generated ‘generic’ profiles (and benchmarks) in this research were to schools in general. In addition, it would also provide further data to confirm if thermal data could be generalised.

The second recommendation would be to establish an automated system to allow the generation of ‘generic’ power demand profiles (and ideally ‘generic’ thermal demand profiles). A GUI would allow the user to enter key building information, select the building category (and sub-category i.e. secondary school, primary school), check whether there is a swimming pool (for schools), IT, whether the building is part of a larger complex and heating type. The model would then produce a series of power demand profiles best suited to represent this school. The profiles would represent typical daily (and weekend), weekly, monthly and annual power demand, as well as how the seasons influence each demand. In addition, performance benchmarks (or matching energy consumption values) would be presented, as well as the various ratings (‘Good’, ‘Very Good’, etc).

Finally the last recommendation would be to apply the ‘generic’ power demand profiles (and benchmarks) to a wider range of non-domestic buildings (hotels, hospitals, universities, retail, etc) and extend its application to countries outside the UK.

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APPENDIX A

1	Time	0:00	0:30	1:00	1:30	2:00	2:30	3:00	3:30	4:00	4:30	5:00	5:30	6:00
2	1/1/2009	10	10	10	10	10	10	10	10	10	10	10	10	10
3	1/2/2009	10	10	10	10	10	10	10	10	10	10	10	10	10
4	1/3/2009	10	10	10	10	10	10	10	10	10	10	10	10	10
5	1/4/2009	10	10	10	10	10	10	10	10	10	10	10	10	10
6	1/5/2009	10	10	10	10	10	10	10	10	12	12	14	14	12
7	1/6/2009	16	16	16	16	16	16	16	16	16	16	16	16	16
8	1/7/2009	18	18	18	18	18	18	16	18	18	16	18	16	16
9	1/8/2009	14	14	14	14	14	14	14	14	14	14	14	14	14
10	1/9/2009	16	16	16	16	16	16	16	16	16	18	18	18	18
11	1/10/2009	16	16	16	16	16	16	16	16	16	16	16	20	18
12	1/11/2009	14	14	14	14	14	14	14	14	14	14	14	14	16
13	1/12/2009	14	16	14	14	14	14	14	14	14	14	16	14	14
14	1/13/2009	14	14	14	14	14	14	14	14	16	14	14	14	14
15	1/14/2009	12	12	12	12	12	12	12	12	12	12	14	14	12
16	1/15/2009	14	14	14	14	14	14	14	14	14	14	14	18	16
17	1/16/2009	10	10	10	10	10	10	10	10	10	10	10	10	10
18	1/17/2009	12	12	12	12	12	12	12	12	12	12	12	12	12
19	1/18/2009	12	14	12	14	14	14	14	14	14	14	14	14	14
20	1/19/2009	14	14	14	14	14	14	14	14	14	14	14	14	14
21	1/20/2009	16	16	16	16	16	16	16	16	16	14	16	14	16
22	1/21/2009	14	14	14	14	14	14	14	14	12	12	12	12	12
23	1/22/2009	18	16	16	16	16	16	16	16	16	16	16	16	16
24	1/23/2009	16	16	16	16	16	16	16	16	16	16	16	16	16
25	1/24/2009	16	16	16	16	18	16	16	16	18	16	16	18	18
26	1/25/2009	14	16	16	14	14	16	16	16	16	16	16	16	14
27	1/26/2009	16	16	16	16	16	16	16	16	16	16	16	16	16

Figure 117 - Sample of raw electricity data

	A	B
10	Reading Date Time	Consumption (m ³)
11	01/09/2010 00:30:00	6
12	01/09/2010 01:00:00	7
13	01/09/2010 01:30:00	7
14	01/09/2010 02:00:00	8
15	01/09/2010 02:30:00	5
16	01/09/2010 03:00:00	7
17	01/09/2010 03:30:00	7
18	01/09/2010 04:00:00	5
19	01/09/2010 04:30:00	8
20	01/09/2010 05:00:00	6
21	01/09/2010 05:30:00	8
22	01/09/2010 06:00:00	5
23	01/09/2010 06:30:00	8
24	01/09/2010 07:00:00	6
25	01/09/2010 07:30:00	8
26	01/09/2010 08:00:00	11
27	01/09/2010 08:30:00	10
28	01/09/2010 09:00:00	10
29	01/09/2010 09:30:00	11
30	01/09/2010 10:00:00	12
31	01/09/2010 10:30:00	11
32	01/09/2010 11:00:00	12
33	01/09/2010 11:30:00	10
34	01/09/2010 12:00:00	8
35	01/09/2010 12:30:00	10
36	01/09/2010 13:00:00	8
37	01/09/2010 13:30:00	8
38	01/09/2010 14:00:00	7
39	01/09/2010 14:30:00	7
40	01/09/2010 15:00:00	7
41	01/09/2010 15:30:00	6
42	01/09/2010 16:00:00	6
43	01/09/2010 16:30:00	6
44	01/09/2010 17:00:00	6
45	01/09/2010 17:30:00	6
46	01/09/2010 18:00:00	6
47	01/09/2010 18:30:00	6
48	01/09/2010 19:00:00	6
49	01/09/2010 19:30:00	6
50	01/09/2010 20:00:00	7
51	01/09/2010 20:30:00	6

Figure 118 - Sample of raw Gas demand data for a school (before conversion into kWh)

Date	Time	Temp Out	Hi Temp	Low Temp	Out Hum	Dew Pt.	Wind Speed	Wind Dir	Wind Run	Hi Speed	Hi Dir	Wind Chill
6/1/2010	0:00	13.2	13.3	13.2	75	8.9	1.3 WNW	2.41	4 W	13.2		
6/1/2010	0:30	13	13.2	13	75	8.7	0.4 W	0.8	3.1 WNW	13		
6/1/2010	1:00	12.8	13	12.8	76	8.7	0.9 WSW	1.61	4 NW	12.8		
6/1/2010	1:30	12.5	12.8	12.5	76	8.4	0.9 SW	1.61	2.7 W	12.5		
6/1/2010	2:00	12.6	12.7	12.4	75	8.3	0.4 NW	0.8	3.1 WNW	12.6		
6/1/2010	2:30	12.6	12.6	12.6	76	8.4	0.9 W	1.61	4 W	12.6		
6/1/2010	3:00	12.6	12.6	12.6	77	8.7	1.3 WSW	2.41	4 NW	12.6		
6/1/2010	3:30	12.2	12.6	12.2	78	8.5	0.9 WSW	1.61	3.1 W	12.2		
6/1/2010	4:00	12.1	12.5	12.1	78	8.3	0.9 SW	1.61	5.4 W	12.1		
6/1/2010	4:30	11.9	12.1	11.8	79	8.4	0.9 WSW	1.61	2.7 WSW	11.9		
6/1/2010	5:00	12.8	12.8	11.9	76	8.7	0.4 WNW	0.8	4 WNW	12.8		
6/1/2010	5:30	12.8	12.8	12.7	78	9	0.4 NW	0.8	2.7 WSW	12.8		
6/1/2010	6:00	12.3	12.8	12.3	83	9.5	0.9 NW	1.61	4.9 WNW	12.3		
6/1/2010	6:30	11.9	12.3	11.8	86	9.6	0.4 W	0.8	3.1 WNW	11.9		
6/1/2010	7:00	11.4	11.8	11.4	87	9.3	0.4 WSW	0.8	1.8 W	11.4		
6/1/2010	7:30	11.2	11.4	11.1	88	9.3	0.4 W	0.8	2.2 W	11.2		
6/1/2010	8:00	11.3	11.3	11.2	89	9.5	0.4 SW	0.8	1.8 WNW	11.3		
6/1/2010	8:30	11.2	11.3	11.2	90	9.6	0.4 SW	0.8	1.3 SW	11.2		
6/1/2010	9:00	11.6	11.6	11.2	91	10.2	0.4 SW	0.8	2.2 W	11.6		
6/1/2010	9:30	11.9	11.9	11.6	91	10.5	0.4 W	0.8	1.3 W	11.9		
6/1/2010	10:00	12.2	12.2	11.9	91	10.7	0.4 SW	0.8	1.8 WNW	12.2		
6/1/2010	10:30	12.4	12.4	12.2	92	11.2	0.4 SW	0.8	2.2 NW	12.4		
6/1/2010	11:00	12.4	12.4	12.3	91	11	0.9 SW	1.61	2.7 WSW	12.4		
6/1/2010	11:30	12.8	12.8	12.4	89	11	0.9 SW	1.61	3.1 WSW	12.8		

Figure 119 - Sample of Weather data (after adjusting for blank data)

1	101	2	67.4	68.4	72.2	73.4	79.2	79.4	78	77.8	78	78.2	78	77
2	102	3	67.6	68.6	73	76	78.8	78.6	77.8	77.6	84.4	87.2	78.2	
3	103	4	67.6	67.8	68.4	70	77.6	77	76.4	76.6	76.4	77.2	76.8	
4	104	5	79.6	78.2	78.2	80	83.6	81.4	82.6	83.4	81.6	80.4	82	81
5	105	6	68.4	67	66.4	66.6	66.8	67	66.2	66.4	66.4	67.2	67.4	72
5	106	7	73.4	73	72.4	72	72.2	71.6	71.2	71.4	71.2	71.2	71.6	71
7	107	1	98	95.2	95.2	95.2	96.4	94.8	96	95	96	106.8	102.6	95
8	108	2	80	80.4	70.8	72.6	79.6	78.4	77.4	77.8	78.4	79.8	79	78
9	109	3	70.4	69.6	68.8	72.6	82.4	80.8	80.6	84.6	90.8	87.6	80.8	80
0	110	4	84	83	83	83.8	84.8	84.4	86.6	84.8	84.8	84.6	83.8	83
1	111	5	63	61.8	61.8	61.8	75.4	73	72.6	73.4	74	74	73.2	73
2	112	6	76	75.4	81.6	81.6	79.4	81.6	80	79	79	81.6	81	
3	113	7	70.4	65.8	65.6	65.8	65.4	65.8	66.8	77.4	74.4	74.6	74.4	74
4	114	1	68.4	66.6	65	66.2	79.2	77.8	77.4	76.2	77	77.2	76	
5	115	2	78	77	70	69	81.6	79.6	79.8	80.4	80.2	80.2	79.8	79
6	116	3	65.8	63.4	64.8	65.6	77.6	75.8	75.6	75.8	76.4	76.2	75.4	
7	117	4	72.8	69.6	71.2	71.2	75.8	71.8	74.2	73	74	73.4	72.2	
8	118	5	81.6	80	68.4	65.6	78.8	71.6	68.8	70	69.8	70.4	69	69
9	119	6	60.8	59.2	60.2	60.8	58.8	58.2	59.6	60	61.6	60	59.4	59
0	120	7	64.4	63	63	62.2	63.2	62.6	62.8	62.2	62	63.4	62.4	61
1	121	1	80.2	71	69.2	70.2	77.2	75.4	78.6	76	77.2	78	77.4	77
2	122	2	84.4	77.2	74.4	75.6	83.4	79	78.4	81.2	80	78.4	79	77
3	123	3	87	86.8	86.6	87	100.2	98.4	97.8	98	98	98.4	97.4	96
4	124	4	108.2	105.6	103.6	102	114.4	114	114.6	112.4	115	113.6	114.4	11
5	125	5	68.4	66.8	70	75.6	90.8	88.8	90.2	90.4	81.6	82.2	81	81
6	126	6	82.6	80.2	80.8	80	81.2	83.2	80.8	81.6	81.8	81.8	82.4	81
7	127	7	80.8	80.2	78	78	77.4	78.4	78	79.8	78.6	79.6	78.6	78
8	128	1	79.6	78.6	77.6	79.4	85	84	83.8	83	84	83	85	82
9	129	2	73.6	71.8	73.8	74.4	82.8	79	79.6	78.2	80.2	77.8	78	79
0	130	3	82.8	80	79.4	88.6	84.8	84.4	81.2	81.2	80.4	78.8	80.4	80
1	131	4	87	86	84.4	87.6	95.8	98.2	99	97.4	97.2	97	97.4	98

Figure 120 - Input data files for the FORTRAN analysing program (demonstrating date and day labelling)

OPTION: 1.											
#School_	0000_WD	0030_WD	0100_WD	0130_WD	0200_WD	0230_WD	0300_WD	0330_WD	0400_WD	0430_WD	0500_WD
Year: 2009											
1	4.60E-03	4.60E-03	4.60E-03	4.70E-03	5.20E-03	5.20E-03	5.20E-03	5.30E-03	5.50E-03	5.70E-03	7.00E-03
2	3.80E-03	3.80E-03	3.90E-03	3.90E-03	3.90E-03	3.90E-03	3.90E-03	3.80E-03	3.60E-03	3.80E-03	4.70E-03
3	4.00E-03	4.00E-03	4.10E-03	4.10E-03	4.10E-03	4.10E-03	4.10E-03	4.10E-03	4.20E-03	4.20E-03	5.00E-03
4	1.30E-02	1.30E-02	1.40E-02	1.40E-02	1.40E-02	1.40E-02	1.40E-02	1.40E-02	1.40E-02	1.40E-02	1.50E-02
5	2.10E-03	2.00E-03	2.00E-03	2.00E-03	2.00E-03	2.10E-03	2.20E-03	2.30E-03	2.30E-03	2.50E-03	3.20E-03
6	5.40E-03	4.80E-03	4.50E-03	4.60E-03	5.00E-03	5.30E-03	5.60E-03	5.40E-03	5.00E-03	4.40E-03	4.40E-03
7	1.20E-02	1.20E-02	1.20E-02	1.20E-02	1.20E-02	1.20E-02	1.20E-02	1.20E-02	1.20E-02	1.20E-02	1.40E-02
8	2.50E-03	2.60E-03	2.50E-03	2.60E-03	2.60E-03	2.70E-03	2.60E-03	2.60E-03	2.60E-03	2.80E-03	3.30E-03
9	3.90E-03	3.90E-03	3.80E-03	3.90E-03	3.90E-03	3.90E-03	3.90E-03	3.90E-03	3.90E-03	4.20E-03	5.00E-03
10	4.30E-03	4.40E-03	4.30E-03	4.30E-03	4.40E-03	4.40E-03	4.60E-03	4.40E-03	4.30E-03	4.30E-03	4.40E-03
11	5.40E-03	5.30E-03	5.30E-03	5.30E-03	5.30E-03	5.30E-03	5.20E-03	5.20E-03	5.20E-03	5.20E-03	5.80E-03
12	2.50E-03	2.50E-03	2.50E-03	2.50E-03	2.50E-03	2.50E-03	2.50E-03	2.50E-03	2.50E-03	2.60E-03	3.00E-03
13	3.10E-03	3.10E-03	3.10E-03	3.10E-03	3.10E-03	3.10E-03	3.20E-03	3.10E-03	3.10E-03	3.40E-03	4.30E-03
14	1.80E-02	1.80E-02	1.70E-02	1.80E-02	1.80E-02	1.80E-02	1.80E-02	2.90E-02	3.70E-02	3.60E-02	3.20E-02
15	3.10E-03	3.10E-03	3.10E-03	3.10E-03	3.10E-03	3.10E-03	3.10E-03	3.10E-03	3.20E-03	3.20E-03	3.90E-03
16	3.20E-03	3.20E-03	3.20E-03	3.20E-03	3.20E-03	3.20E-03	3.40E-03	3.50E-03	4.10E-03	5.20E-03	6.50E-03
17	1.60E-02	1.60E-02	1.60E-02	1.60E-02	1.60E-02	1.60E-02	3.40E-02	2.60E-02	2.20E-02	2.10E-02	2.20E-02
18	1.10E-02	1.10E-02	1.10E-02	9.90E-03	8.90E-03	8.60E-03	7.80E-03	8.00E-03	7.80E-03	7.00E-03	7.30E-03
19	3.60E-03	3.60E-03	3.60E-03	3.60E-03	3.60E-03	3.60E-03	3.60E-03	3.60E-03	3.70E-03	3.90E-03	4.50E-03
20	7.20E-03	7.20E-03	7.20E-03	7.40E-03	7.70E-03	7.80E-03	7.90E-03	8.10E-03	8.20E-03	8.90E-03	1.10E-02
21	2.10E-03	2.10E-03	2.20E-03	2.20E-03	2.20E-03	2.20E-03	2.10E-03	2.10E-03	2.20E-03	2.20E-03	2.40E-03
22	2.80E-03	2.80E-03	2.80E-03	2.80E-03	2.80E-03	2.80E-03	2.80E-03	2.70E-03	2.70E-03	2.80E-03	4.00E-03
23	5.60E-03	5.60E-03	5.70E-03	5.70E-03	5.70E-03	5.80E-03	6.70E-03	6.70E-03	7.10E-03	7.20E-03	7.40E-03

Figure 121 - Sample FORTRAN analysing program output file (demonstrating school number and output selection)