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Multi-scale analysis of the energy performance of supermarkets

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MULTI-SCALE ANALYSIS OF THE ENERGY PERFORMANCE OF SUPERMARKETS

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

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As you set out for Ithaka
hope the voyage is a long one,
full of adventure, full of discovery.

(Extract from the poem Ithaka by C.P. Cavafy)

As I set out for my own Ithaka, which was indeed a long, full of adventure and discovery process, I had my very own army of supporters to keep me going. I would like to thank my supervisor, Professor Malcolm Cook, for being by my side from the beginning until the end of the project, providing support and feedback along the way; Richard Lee, for conceiving this project and for all the project and personal development support he has provided me with; Dr Kirk Shanks, for sticking with me, even though he moved to Dubai while we were working on the Energy & Buildings paper; and Professor John Mardaljevic, for being there to answer all of my questions, and proofreading most of my work.

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Ithaka gave you the marvelous journey.
Without her you would not have set out.
She has nothing left to give you now.
And if you find her poor, Ithaka wont have fooled you.
Wise as you will have become, so full of experience,
you will have understood by then what these Ithakas mean.

(Extract from the poem Ithaka by C.P. Cavafy)

ABSTRACT

The retail sector accounts for more than 3% of the total electricity consumption in the UK and approximately 1% of total UK CO_2 emissions. The overarching aim of this project was to understand the energy consumption of the Tesco estate (the market leader), identify best practice, and find ways to identify opportunities for energy reduction.

The literature review of this work covered the topic of energy consumption in the retail sector, and reviewed benchmarks for this type of buildings from the UK, Europe and the US. Related data analysis techniques used in the industry or presented in the literature were also reviewed. This revealed that there are many different analysis and forecasting techniques available, and that they fall into two different categories: techniques that require past energy consumption data in order to calculate the future consumption, such as statistical regression, and techniques that are able to estimate the energy consumption of buildings, based on the specific building's characteristics, such as thermal simulation models. These are usually used for new buildings, but they could also be used in benchmarking exercises, in order to achieve best practice guides. Gaps in the industry knowledge were identified, and it was suggested that better analytical tools would enable the industry to create more accurate energy budgets for the year ahead leading to better operating margins.

Benchmarks for the organisation's buildings were calculated. Retail buildings in the Tesco estate were found to have electrical intensity values between 230 kWh/m^2 and 2000 kWh/m^2 per year. Still the average electrical intensity of these buildings in 2010-11 was found to be less than the calculated UK average of the 2006-07 period. The effect of weather on gas and electricity consumption was investigated, and was found to be significant ($p<0.001$). There was an effect related to the day-of-the-week, but this was found to be more related to the sales volume on those days. Sales volume was a proxy that was used to represent the number of customers walking through the stores. The built date of the building was also considered to be an interesting factor, as the building regulations changed significantly throughout the years and the sponsor did not usually carry out any fabric work when refurbishing the stores. User behaviour was also identified as an important factor that needed to be investigated further, relating to both how the staff perceives and manages the energy consumption in their work environment, as well

as how the customers use the refrigeration equipment.

Following a statistical analysis, significant factors were determined and used to create multiple linear regression models for electricity and gas demands in hypermarkets. Significant factors included the sales floor area of the store, the stock composition, and a factor representing the thermo-physical characteristics of the envelope. Two of the key findings are the statistical significance of operational usage factors, represented by volume of sales, on annual electricity demand and the absence of any statistically significant operational or weather related factors on annual gas demand. The results suggest that by knowing as little as four characteristics of a food retail store (size of sales area, sales volume, product mix, year of construction) one can confidently calculate its annual electricity demands (R^2=0.75, $p<0.001$). Similarly by knowing the size of the sales area, product mix, ceiling height and number of floors, one can calculate the annual gas demands (R^2=0.5, $p<0.001$). Using the models created, along with the actual energy consumption of stores, stores that are not as energy efficient as expected can be isolated and investigated further in order to understand the reason for poor energy performance.

Refrigeration data from 10 stores were investigated, including data such as the electricity consumption of the pack, outside air temperature, discharge and suction pressure, as well as percentage of refrigerant gas in the receiver. Data mining methods (regression and Fourier transforms) were employed to remove known operational patterns (e.g. defrost cycles) and seasonal variations. Events that have had an effect on the electricity consumption of the system were highlighted and faults that had been identified by the existing methodology were filtered out. The resulting dataset was then analysed further to understand the events that increase the electricity demand of the systems in order to create an automatic identification method. The cases analysed demonstrated that the method presented could form part of a more advanced automatic fault detection solution; potential faults were difficult to identify in the original electricity dataset. However, treating the data with the method designed as part of this work has made it simpler to identify potential faults, and isolate probable causes. It was also shown that by monitoring the suction pressure of the packs, alongside the compressor run-times, one could identify further opportunities for electricity consumption reduction.

KEY WORDS

Supermarkets; Retail outlets; Energy performance; Energy consumption; Refrigeration; Statistical analysis; Regression

PREFACE

The research presented by this discourse was conducted to fulfil the requirements of an Engineering Doctorate (EngD) at the Centre of Innovative and Collaborative Construction Engineering (CICE), Loughborough University. The research programme was supervised by CICE at Loughborough University and funded by the Engineering and Physical Sciences Research Council (EPSRC) as well as Tesco PLC.

The main aim of the EngD is to solve one or more significant and challenging engineering problems with an industrial context. The EngD is an alternative to the traditional PhD, as it requires the researcher to be positioned within a sponsoring organisation guided by an industrial supervisor while academic support is provided by regular contact with academic research supervisors.

The EngD is examined on the basis of a discourse supported by publications or technical reports. This discourse is supported by two conference, and one journal papers [1] [2] [3]. The papers have been numbered 1-3 for ease of reference and are located in Appendices A to C of the discourse. While references to the papers are made throughout the discourse, there are key reference points in section 2 where the reader is directed to read each paper in its entirety and then return to this thesis. This is intended to reduce the need for the reader to constantly refer to the accompanying papers while reading the discourse.

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List of Papers

The following papers, included in the appendices, have been produced in partial fulfilment of the award requirements of the Engineering Doctorate during the course of the research.

Paper 1: See Appendix A

Spyrou, M., Cook, M. J., Shanks, K., Lee, R., & Conlin, J. (2011). Energy Consumption Prediction Models for the Retail Sector. In CIBSE Technical Symposium, DeMontfort University, Leicester UK - 6th and 7th September 2011.

Paper 2: See Appendix B

Spyrou, M. S., Shanks, K., Cook, M. J., Pitcher, J., & Lee, R. (2014). An empirical study of electricity and gas demand drivers in large food retail buildings of a national organisation. Energy and Buildings, 68, 172182. doi:10.1016/j.enbuild.2013.09.015

Paper 3: See Appendix C

Spyrou, M. S., Cook, M. J., Mardaljevic, J., McMullen, A., Lee, R., Pitcher, J. (2015). The Operational Efficiency of Commercial Food Refrigeration Systems: A Data Mining Approach. ASHRAE Winter Conference 2015, 24-28 January, Chicago, USA.

Chapter 1: Introduction

1.1 Background to the Research

1.1.1 The General Subject Domain

From large multiples to small independent retailers, the UK grocery market's share accounts for 54.5p in every £1 of UK retail spending and it was worth £174.5 billion in the year between April 2013 and April 2014. During the same year there were more than 9000 food retail stores with sales floor areas larger than 280 m^2. Most of these stores are operated by the four largest supermarket multiples, Tesco (market share: 28.9%), ASDA (17%), Sainsbury's (16.6%) and Morrisons (11%) [4] and [5]. The remaining 26.5% of the market is shared by smaller chains such as Waitrose, Iceland and Aldi [4]. The profit margins these organisations are working to have been reported to an average of 4.8% in 2012 [6], spend on energy is approximately 15% of the trading profit, therefore the energy consumption of their stores is important for the profitability of the organisations. Additionally the consumption is important for national CO_2 emission targets where the grocery retail sector accounts for more than 3% of the total electricity consumption in the UK and approximately 1% of total UK CO_2 emissions [7]. Considering both these issues, along with the relative homogeneity of management structures and energy end-uses in food retail organisations, managing and minimising energy demand is an important consideration for both national targets and business competitiveness.

1.1.2 The Industrial Sponsor

Tesco was founded in 1919 by Jack Cohen as a one-man business. It has grown over the years and it currently operates in 12 countries employing more than half a million people. As a large organisation, Tesco affects millions of people's lives every day. As Philip Clarke, Tesco's CEO between 2011 and 2014, said

"Our scale gives us [Tesco] an opportunity to make a positive difference to some of the biggest challenges facing the world."[8].

One of the ways the organisation aims to make a positive change is by reducing its carbon emissions. Tesco has set a target of reducing its carbon emissions by 50% by 2020 (based on a 2006 baseline) and has pledged to become a zero-carbon business by 2050 [9]. Since there is no official scientific explanation for zero-carbon, it is suggested that Tesco is aiming to become a carbon neutral business. Oxford English Dictionary defines “carbon neutral” as:

“Making or resulting in no net release of carbon dioxide into the atmosphere, especially as a result of carbon offsetting.”

For a company of this size, it is a significant challenge to become carbon neutral as there are many factors affecting their footprint, such as the electricity consumption of stores and offices, refrigerants, transportation of products, and even business travel [10]. In 2010 the total electricity consumption of all the UK Tesco stores amounted to 1% of the UK’s energy consumption [7]. Therefore, it is significant to note that by reducing Tesco’s electricity consumption by 10%, the consumption of the UK can be reduced by 0.1% (0.3 TWh). Their ambitious carbon reduction programme encompasses both new and existing stores as well as operations; working to improve the design of their new stores, replacing the equipment in their existing stores, reducing the electricity and gas use- either by making the buildings more energy efficient, or by using renewable sources of energy; reducing the use of refrigerant gas in the refrigeration systems, reducing delivery van trips undertaken to move goods around, etc.

In 2014 Tesco was operating 3,378 stores in the UK [11]. These stores ranged in age and size, and although well developed energy management strategies are applied, the consumption of energy to operate these buildings forms a large part of the overall carbon emissions of the organisation.

1.1.3 The Context of the Research

Strategic financial planning in the sector’s large organisations typically takes account of future demands for gas and electricity. Future demands and financial implications are estimated for different time frames, such as the months or year ahead, and account for increasing energy prices, changes in store sizes and reductions due to investment in energy efficiency initiatives applied across an organisation’s building stock. Projected energy demands are used for multiple purposes including the identification of the operational efficiency of individual stores indicating generally where inefficiencies lie and when faults occur.

This work initially looked at the wider grocery retail sector to understand how the industrial sponsor performed compared to its peers. It looked at benchmarks from organisations around the US and Europe and compared the sponsor’s performance against them. It then concentrated on the electricity and gas consumption of the sponsor itself; various studies were carried out in order to understand the data available, and the different factors that influence electricity and gas consumption. This was completed by looking at different samples of stores. It was identified that the refrigeration consumption was the largest driver of electricity consumption, and one that the sponsor understood the least, therefore, for the last part of the project, the consumption and operation of the refrigeration systems was put to scrutiny in order to find inefficiencies.

The scope of the work undertaken is graphically summarised in Figure 1.1, indicating how the work was focussed towards the end of the project.

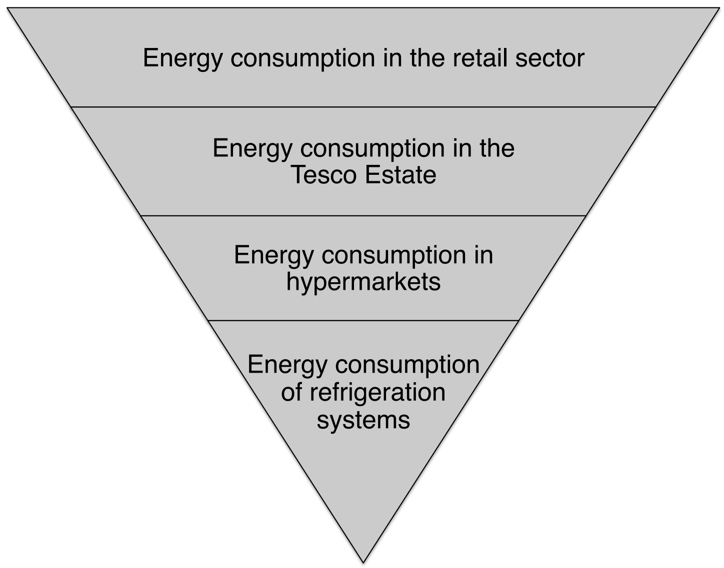

Figure 1.1: Scope of work throughout the project

1.2 Aim and Objectives

The aim of this project was to understand the energy consumption of the Tesco estate, identify best practice and find ways to identify opportunities for energy reduction. The specific objectives of this project are detailed below:

Objective 1:

Identify and critically assess the literature and current practices in energy consumption analysis and benchmarking

Objective 2:

Analyse existing energy consumption data for the Tesco estate and establish correlations with possible drivers (such as weather, time of year, sales etc.)

Objective 3:

Develop and implement a methodology for characterising the energy consumption of stores and identifying outliers

Objective 4:

Develop and implement a methodology for identifying conditions in refrigeration systems that lead to increased energy consumption and find early warning signs to be used as part of a proactive maintenance routine

Figure 1.2 presents an overview of the work undertaken, and how each objective was broken down and achieved.

1.3 Research Justification

Tesco, and the retail industry in general, have vast quantities of energy data resulting from sub-metering carried out on most of their sites. This project has been designed to make use of this data and provide a more detailed understanding of the main drivers of energy consumption in Tesco stores than what currently exists. It is intended that this work will enable the identification of stores and equipment that are inefficient and performing outside of best practice in order to deliver better control and energy reduction targeting.

1.4 Thesis Structure

Chapter 1 of this thesis has introduced the work, including the background to the research, the general subject domain, the industrial sponsor and the context of the research. The aims and objectives of the work were also presented and justified. Chapter 2 presents related work in the general topic of energy consumption in the retail sector, including a summary of the analysis and prediction techniques used both in the industry and the literature. The adopted methodology is discussed in Chapter 3, and the methods used in each study are presented in detail.

Chapter 4 is considered as the main body of this work and presents the research undertaken throughout this project. Similarly to Chapter 3, Chapter 4 is divided into seven studies, detailing the work carried out for each objective. Key findings and implications are presented in Chapter 5, where the contribution to the existing theory and practice is also highlighted. This chapter concludes the discourse with recommendations for the industry and further research, along with a critical evaluation of the research undertaken.

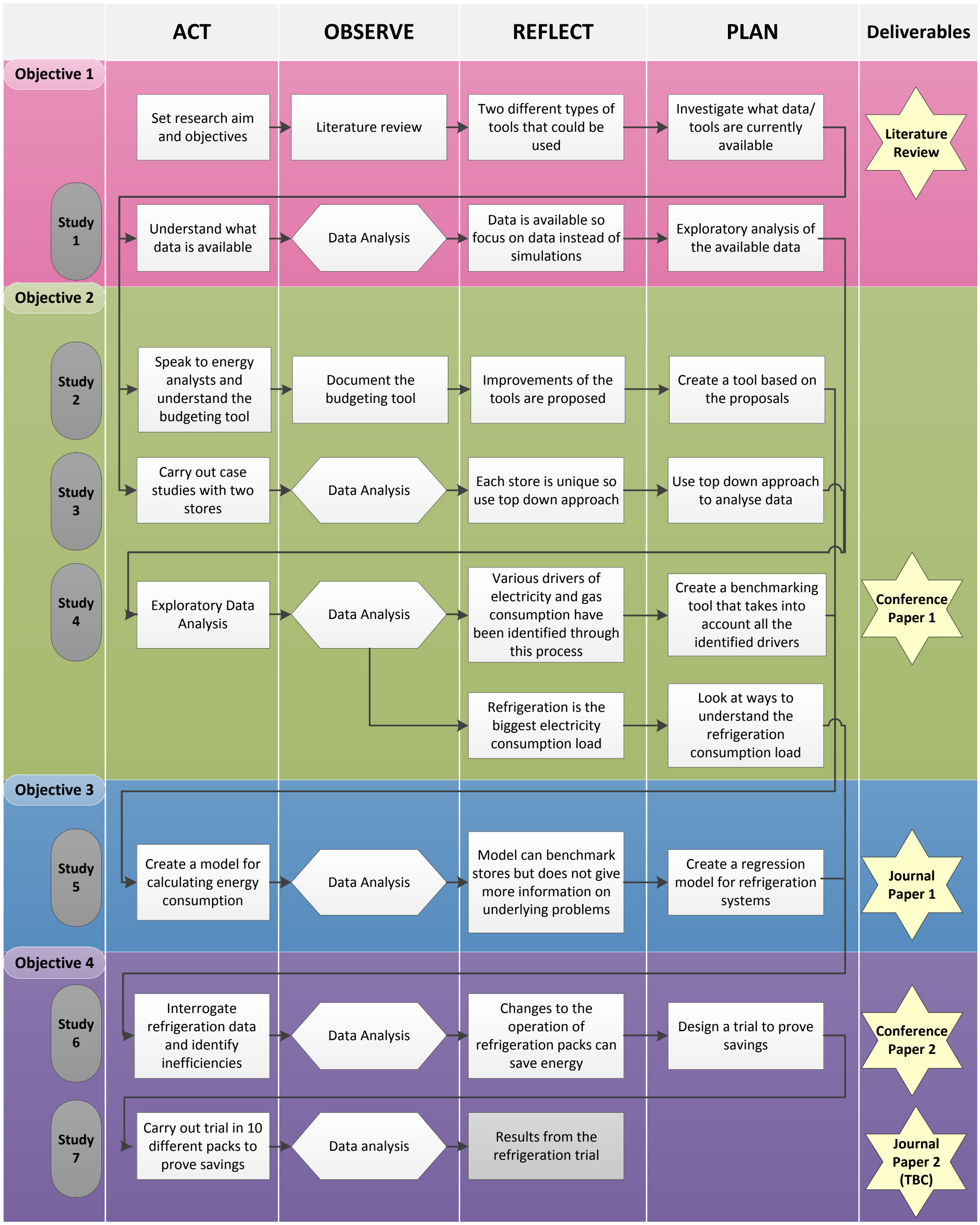

Figure 1.2: Map of the research undertaken

Chapter 2: Related Work

This chapter summarises the findings of the literature review carried out at the beginning, and throughout this project. This review aims to identify the status of the retail industry in relation to energy consumption benchmarks and to identify the state of the art methods for analysing and predicting the energy consumption of buildings. The initial literature review was presented as a conference paper [1] which can be found in Appendix A and should be read alongside this section.

2.1 Energy Consumption Benchmarks for the Retail Sector

British retailers are impacted by three government regulations addressing the energy consumption in the sector, as suggested by the British Retail Consortium website [12]; the mandatory Greenhouse Gas Emissions (GHG) reporting, the Carbon Reduction Commitment (CRC) Energy Efficiency scheme, and the Energy Performance in Buildings Directive (EPBD). More recently large retailers have also been impacted by Energy Savings Opportunity Scheme (ESOS) the UK implementation of Article 8 of the 2012 EU Energy Efficiency Directive (EED) [13].

The mandatory GHG reporting is a scheme that requires all companies listed on the main market of the London Stock Exchange to provide annual GHG emissions reports from 1 October 2013. The CRC Energy Efficiency Scheme is again a mandatory scheme aimed at promoting energy management and efficiency within large and medium sized organisations. The ESOS mandates all large businesses in the UK to undertake comprehensive assessments of energy use and energy efficiency opportunities at least once every four years.

The EPBD was introduced to drive a reduction in energy use and carbon dioxide emissions in both private and public commercial buildings, and places a requirement for all properties to have an Energy Performance Certificate (EPC) when sold, built or rented. EPCs rate a building's theoretical performance against benchmarks for the same type of building (similar to an asset rating). During the EPC rating, the building in question is described using a semi-dynamic model (which uses building material performance characteristics, as well as the area of the building) and is then benchmarked against other buildings of the same type. The EPCs have been criticised since their introduction as the assessor can use more than one software program to reach the EPC rating, and different software programs have been found to produce different results; Raslan and Davies provide a comprehensive review [14]. Additionally the retail sector has criticised EPC because they only take the regulated loads into account, which, in the case of food retail, means that the consumption, gains, and losses of refrigeration systems are not taken into account. Taking into account the food refrigeration systems in a building is important for the retail sector as this makes up between 30% and 50% of the total load as explained in Chapter 4.

There are various methods and standards used in the industry for benchmarking the energy intensity of retail buildings, including EPC, CIBSE TM46, International Sustainability Alliance (ISA) (funded by Building Research Establishment (BRE)), and ASHRAE benchmarks. Berman, Mumovic and Kimpian have looked at the UK and US methodologies for a sample of buildings and have provided a comprehensive review [15]. The techniques employed to create and assess the predictions obtained using these benchmarking and forecasting methods are described and discussed in Appendix A, Sections A.2.1 to A.2.3. In summary, it was found that the various organisations internationally provide benchmarks in different units, and use a breadth of different techniques in their calculations. The methods for calculating/estimating the floor area for the benchmarks differ for each organisation. For example, TM46 Energy Benchmarks assumes that the internal sales floor area is half that of the total floor area, while the European Commission for Energy defines the area of buildings in square meters of useful floor area (which excludes construction areas, functional areas for ancillary use and thoroughfares) [16, 17, 18, 19]. The benchmark values from these organisations were found to range from 505 kWh/m^2 [17] to 955 kWh/m^2 [20] depending on the organisation publishing the values. This indicates that benchmarking the energy intensity of retail buildings is not a straightforward task; new and more uniform ways of calculating benchmarks for the retail sector are needed. These should be able to take into account retail specific plug loads (i.e. refrigeration load) as well as the effect of the interaction between Heating Ventilation and Air Conditioning (HVAC) and food refrigeration.

2.2 Analysis and Prediction Techniques

The ability to analyse and accurately predict future events is becoming increasingly important for businesses in the recent years as most management decisions and business forecasts depend on them. In the case of the retail industry, companies need to be able to analyse, predict and reduce the buildings' energy consumption, as the electricity and gas prices have been on an increasing trend. This has put more focus on sustainability and energy efficiency opportunities. Analysis tools include statistical models, such as regression, the use of neural networks, and the use of spreadsheet models and other similar tools used by the majority of retailers. Appendix A, Section A.2.5 presents the various ways for analysing and predicting the energy consumption mentioned in the literature in more detail.

Commonly, the data analysis techniques include statistical or empirical models. These models use measured (observed) data to summarise the properties of the system (or building) in a graph, a table or a curve fit to observation points, and they assume knowledge of the fundamental quantitative trends but lack accurate understanding [21]. A simple model is for example an equation that represents the linear relationship between two variables, a linear regression model.

Other modelling tools include Multiple Linear Regression (MLR), which is an extension of the simple linear regression; Multivariate Adaptive Regression Splines (MARS), a non-linear regression method; Artificial Neural Networks (ANNs) which is a black-box type of forecasting tool. Fischer et. al. arrived at the conclusion that even though ANNs and MARS produce comparable results, MARS is considerably faster and much easier to use for this type of work [22]. The Autoregressive Integrated Moving-Average (ARIMA) is another class of linear models that is often used in analysis and forecasting. They were firstly presented by Box and Jenkins in 1970 [23].

A useful summary of data analysis and simulation models for energy data analysis is provided by Reddy. Reddy presents the reader with a review of the classical statistical concepts (e.g. regression, time-series analysis, ANNs), an understanding of the model building process, the system optimisation process and the clustering process for different systems/buildings. Reddy is able to provide the reader with the practical understanding and confidence in being able to interpret their numbers and understand how their systems/buildings are performing. [21]

2.3 Energy Performance Simulation

What has been presented so far requires the use of in-use energy consumption data to predict the energy consumption for the future. In the building and construction industry, energy performance simulation software packages are often used during the design process in order to estimate the future energy consumption of a building. These software packages are able to estimate the energy consumption of buildings, using the laws of physics, with the user importing various attributes for the simulation, such as building dimensions, building materials, equipment installed and occupancy levels. These tools usually have preloaded weather information for average years, including air-temperature, solar radiation, and rainfall.

Various authors have used Dynamic Thermal Simulation (DTS) tools for estimating the energy consumption of buildings. For example Wang et. al. have used one such tool, EDSL Tas V9.0.9, to build a model of a typical retail shed [24]. Similarly, Fumo et. al. used EnergyPlus to estimate the hourly energy consumption of a building, using monthly data [25]. Using this method, the user does not have to import the various parameters for the building, but select a benchmark model building from the ones preloaded on EnergyPlus. The monthly utility bills were used for estimating the hourly building consumption, and EnergyPlus was then used to estimate the energy consumption for the same time scale. The two values were then compared to each other to produce magnitude and frequency of errors.

Neto and Fiorelli carried out a comparison between detailed model simulation (using EnergyPlus) and ANNs for forecasting building energy consumption. They concluded that ANNs have a 3% lower average error, and that the effect of external temperature is more significant than those of humidity and solar radiation [26] proving that both methods can be used for forecasting building energy demands.

Examining the literature, many authors have reviewed the thermal simulation tools available; for example Crawly et. al. reviewed 20 of these simulation programs, including EnergyPlus, ESP-r, IES-VE, Tas and TRNSYS [27]. The authors stress the fact that many users rely on just one simulation tool, but they advise them to use a combination of tools so that they have a better view of their buildings' performance. The aforementioned simulation tools seem to have the most relevant simulation features, with TRNSYS being the only one able to model 12 different renewable energy systems.

A more comprehensive inquiry and an ongoing one, is a US initiative called "The Building Energy Software Tools Directory". This directory, compiled for the US Department of Energy, provides information on more than 350 building software tools for evaluating energy efficiency, renewable energy, and sustainability in buildings. [28]

2.4 Exception Reporting and Fault Diagnosis

Exception reporting and fault diagnosis is a large area of work and depending on the industry, different authors use different methods. The objective of these methods is to be able to identify abnormal behaviour of a system, usually resulting from a mechanical fault or incorrect usage of the equipment.

In the case of energy consumption data, Lowry and Fiorelli use ARIMA models (described earlier in Section 2.2) to interpret the energy data in hand. The authors check for periodicity or seasonality in the data using Fourier analysis, followed by a confirmation from an autocorrelation function. They analyse the patterns observed and demonstrate how this can be used in exception reporting. Lowry and Fiorelli present very promising results using the ARIMA models for the electrical consumption of office buildings, but their model has a weakness; they only use data for four months, during spring, so they avoid big changes in the consumption due to weather changes. It would be interesting to see how well this model copes with weather, maybe using a larger time scale and a building that has a wider range of energy consumption throughout the year.[29]

In the more specific case of refrigeration units/systems, a lot of work has been undertaken in order to create models to represent how the systems are working and estimate/optimise their electricity demand. For example Larsen, Jakobsen, Hovgaard and others [30, 31, 32, 33, 34, 35] look specifically into how refrigeration systems operate and how they can be optimised. Li and Braun, as well as Wichman and Braun [36, 37, 38, 39] have done a lot of work on fault detection and diagnosis, especially on heating and cooling systems. Their methods involve a physical as well as a theoretical model where faults are being implemented/simulated. They are able to decouple the effects of various faults and identify them separately in the systems they are investigating.

Thybo and Izadi-Zamanabadi have looked at the various Fault Detection and Diagnostics (FDD) tools applicable for refrigeration systems and divided them into three types; experimental evaluation and analysis of past events; theoretical work based on "state of the art" FDD methods; and heuristic fault detection evaluation based on their field experience[40]. They have also discussed the constraints and scalability of each method and concluded that a model-based approach was better than a data classification and pattern recognition approach because of the robustness requirements and the constrains of generalisation of the latter approach, as well as the fact that their team had the knowledge about the system they were modelling. Thybo and Izadi-Zamanabadi concluded that the model-based approach was a step towards real time fault detection in refrigeration systems, while raising concerns about the scalability of the method. [40]

2.5 Summary

A review of the literature covered the energy consumption in the retail sector, energy benchmarks and various prediction and fault detection tools. It was found that benchmark values for electricity and gas consumption of retail buildings are calculated using different methods and standards in different countries and that a more uniform approach would be beneficial. This review has also presented many different energy analysis and forecasting techniques and divided them into two different categories: techniques that require past energy consumption data in order to calculate the future consumption, such as statistical regression; and techniques that are able to estimate the energy consumption of buildings, based on the specific building's characteristics, such as thermal simulation models.

Gaps in the industry were recognised, and it was suggested that better analytical tools would enable the industry to create more accurate energy budgets for the year ahead leading to better operating margins. More sophisticated techniques in forecasting the energy consumption of retail buildings should incorporate the various factors affecting the energy consumption, including but not limited to: outside air temperature, sales figures, built date and day-of-the-week profiles. The forecasting ability of Artificial Neural Networks cannot be undervalued, even though their ability to generalise, or produce accurate results for prolonged periods of time has not been demonstrated so far. This is usually affected by the quality of the training data set as well as the experience of the model developer. The focus of future work will therefore concentrate on the various statistical techniques presented. Hence, the first part of the project was aimed at understanding the current status of consumption in the organisation's estate.

Fault detection methods were also discussed and it was found that there is a gap in the literature for a simple and scalable method that enables fault detection. For this reason, the second part of this project was aimed at creating a simple fault detection method to enable the detection and identification of faults that caused an increase in the energy consumption of refrigeration systems.

Chapter 3: Methodology

3.1 Overview

This chapter introduces the overarching methodology selected for addressing the research objectives outlined in Section 1.2, providing a systematic route for conducting the research. The EngD programme requires that the project demonstrates innovation in the application of knowledge to the business environment, resulting in the need for a flexible approach to research. [41]. This approach is aligned with O'Leary's cycles of action research, which are shown in Figure 3.1. As shown earlier, Figure 1.2 illustrates the key stages in the research process for this EngD, highlighting the cyclic nature of the methodology focused on observations, reflections, planning and actions (feeding back into observations and so forth). This process has resulted in seven studies to be completed as part of this project; after each study a thinking/planning stage allowed for critical decisions to be made regarding the direction of the project. Each study (numbered 1-7 in the diagram) is discussed in detail in Chapter 4. Study 1 was completed to address Objective 1, Studies 2 - 4 were completed to address Objective 2, Study 5 addresses Objective 3, while Studies 6 and 7 address Objective 4.

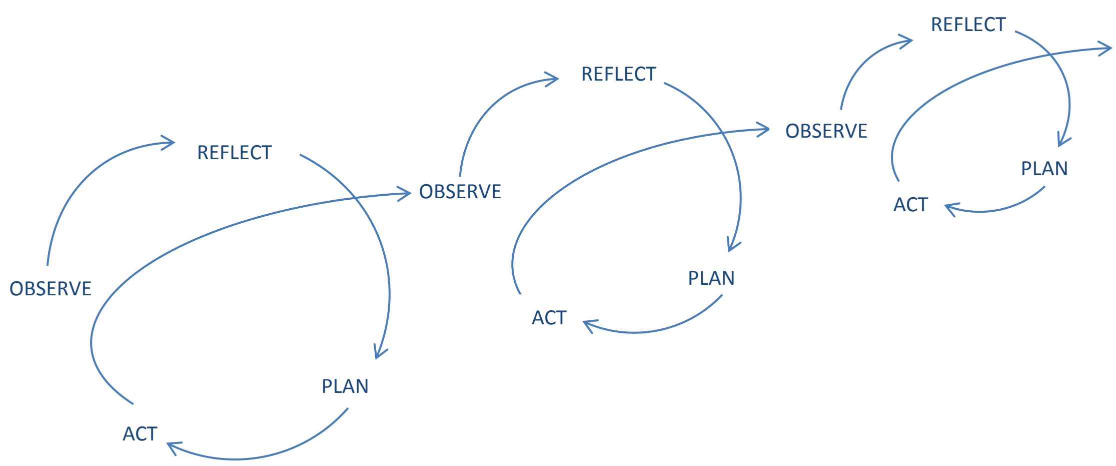

Figure 3.1: O'Leary's cycles of research adapted from [42]

3.2 Methods used

A variety of methods were used in this project and in order to be consistent throughout the whole of this discourse, the precise methods and tools used for each study are presented and discussed in Sections 3.2.2 to 3.2.7. A description of the available data for this project is included in Section 4.1 alongside the various data collection and pre-processing methods applied by the sponsor organisation.

3.2.1 Literature Review

The literature review is a fundamental method for any research project as it highlights previous and parallel research efforts related to the research topic, and provides a foundation for the work to be carried out. An initial literature review was carried out at the beginning of the project (Chapter 2) looking at the status of the retail industry in relation to energy consumption benchmarks and the state of the art methods for analysing and predicting the energy consumption/intensity of buildings. Further reviews supplemented the initial review throughout the duration of the research. These addressed the specific needs of the individual studies (for example focussing on refrigeration for the last two studies) whilst also ensuring that parallel publications were considered as soon as they became available. These reviews can be found as part of each publication in Appendices A, B and C.

3.2.2 Study 1: Data Available to this Research Project

The first study completed for this project was an extension of the literature review as it looked into the various data relevant to this project and available through Tesco's databases. Data identification was conducted through unstructured interviews with energy managers, energy analysts and database managers. Unstructured interviews were conducted as they allowed the conversation to develop and enabled the responder to express their opinions regarding various data that could be used for the purpose of the project. Data source selection and data gathering was conducted separately for each study, according to decisions made before or during the planning stage of each study. Exploratory research methods were fundamental for this project as it was necessary to understand what data was available to the researcher and what it was representing. Study 1 details all of the available data, what it represents, the frequency intervals at which it is recorded and discusses its robustness and usability.

3.2.3 Study 2: Current Practices for Energy Modelling in Tesco

The second study extended the literature review again, with the aim to understand the current practices for energy modelling within the sponsor organisation. Current practises were explored through unstructured interviews with the data analysts, and close interrogation of the energy budgeting tool they were producing using Microsoft Excel. The tool was investigated fully and mathematical equations were produced for each step of the process.

3.2.4 Study 3: Analysis of the Electricity Consumption of two Supermarkets

Case study research focuses on a specific group, person or organisation and offers an in-depth investigation and analysis of a specific aspect or problem [43]. Case studies can be used by researchers to delve deeper within the area of study in order to provide insights that other methods cannot [44]; this is of particular relevance to the EngD research. In the third study, a case study methodology was used to analyse data for two stores from 2006 to 2011 in order to understand how their consumption changed over the years. Two stores were selected because they were of similar size but at different parts of the country. Another requirement was the availability of submetered data for the stores for more than two years. For the purpose of the work in Study 3, weekly electricity and sub-metered data were obtained through Database 1, Figure 4.1, for the period of 1/3/2006-1/3/2011. The dates were chosen because they formed the latest Tesco period at the time of the analysis. Outside air temperature was used as the average temperature of the week for the region. Energy efficiency project data were provided by the energy analysts in the form of project title, project description and installation week.

The focus of Study 3 was the electricity consumption of the stores, and the factors that affected it across the years. The electricity consumption data of the stores was plotted against time, and the energy efficiency projects installed in those stores were mapped on top of the electricity data. Where there was a spike, or an interesting event in the data, a close inspection of the data took place, looking into the electricity consumption in half-hourly time intervals and the effect of each of the energy efficiency projects on it.

3.2.5 Study 4: Analysis of the Available Data for the whole Estate

Exploratory analysis was used for this study. Exploratory Data Analysis (EDA) is an approach for analysing datasets, usually with visual methods, to summarise their main characteristics. It allows the researcher to understand what the data ‘wants to say’, and identify any underlying structures. EDA depends heavily on graphs because visual inspection offers special insight into the data, but it also uses many numerical techniques. Both the visual and numerical techniques focus on searching for knowledge that allows for more effective testing of theories and hypotheses.[45]

Study 4 was designed with the aim of understanding if and how different factors/variables affect the energy consumption of stores. For that reason, weekly electricity, gas and sub-metered data for the period of 1/3/2010-1/3/2011 were obtained through the Database 1, Figure 4.1. Degree-day data was obtained from BizEE [46] for station EGLL at Heathrow Airport to represent the outside air temperature. The weather station was chosen for its proximity to the majority of the stores, while the dates were chosen because they formed the latest Tesco period at the time of the analysis. Physical characteristics of the stores were obtained from Database 4, Figure 4.1, and these included type and size of the store amongst others.

As suggested by Reddy [21] the sample was initially screened graphically, and any outliers observed were investigated before the analytical screening of values that were outside the 3 x standard deviation range was carried out. The investigation included a check that the consumption data was in line with the monthly bills of the store, a check that the sales area of the store was in line with the architectural design and more. The compiled values were checked for quality and completeness. Any stores that had incomplete datasets were eliminated. This eliminated stores that were built in the year 2010-11, as well as stores with sub-metering issues. Stores that were extended/reduced in SFA within the year were also excluded, as these would have brought inaccuracies in the calculations. Another quality measure was the availability of SFA data for the store. If the SFA data was not available, and no architectural design was available to extract the data from, the store was excluded as well. Following quality control checks, the number of stores included in the study was still significant; Electricity data, N_{elec}=1518 out of a total of 2123 stores, while gas data, N_{gas}=411 out of approximately 900 stores that are gas-heated.

3.2.6 Study 5: Modelling the Energy Consumption of Hypermarkets

Study 5 is a further development of Study 4 as it attempted to predict the consumption (dependent variable) from a list of identified independent variables, such as weather and size of the store. Statistical tests were applied to groups of dependent and independent variables to identify correlation significance of store characteristics, drivers of demand, and goodness of fit of resultant regression equations. The dependent variables investigated were Electricity Consumption and Gas Consumption. Stepwise linear regression was used to identify the significance of proposed independent variables which were selected on the basis of engineering understanding of energy demands along with factors identified in the previous studies. A table of all the variables is included in Appendix B Table B.3.1.2. These tests informed the design of multiple linear regression models where analysis of the dependent variables resulted in three parallel equations; the independent variables included in each equation varied in relation to the dependent variable being investigated.

Measurements of all variables were compiled for each hypermarket store, N=215 (at the time of the analysis). The study dataset was then checked and adjusted for quality and outliers. From the initial sample, stores with missing values were removed (N=12), similar to stores that had undergone any type of development works (extension or remodelling) within the period investigated (N=9). With the remaining dataset, standardised procedures were used to detect outliers where any data values more than 3 standard deviations from the mean were individually investigated. Whilst most of the data points falling outside of this range were found to be valid measurements, a number of these (N=6) were not. These were found to be measurements of stores within shopping centres where possibly the measurements included consumption of the whole shopping centre and not just the stores in question, and they were therefore removed. This procedure ensured that stores that had experienced technical faults or structural changes in end-use energy systems or measurement systems were removed from the study sample dataset. This resulted in a complete study sample for electricity of N_{elec} =188 and a study sample for gas of N_{gas}=123, as complete gas consumption data was not available for 65 stores.

All variables were tested for linearity and normality [1] and it was confirmed that all dependent and independent variables fulfilled the requirements of parametric tests, except Gas Consumption. Gas Consumption was found to have a bimodal distribution, which when investigated revealed significant differences between stores with Combined Head and Power (CHP) plants and those without. Separate analysis was therefore carried out for stores grouped according to the presence or absence of a CHP plant.

Stepwise linear regression, along with regression diagnostics, was conducted using SPSS [47]. This automated procedure resulted in automatic exclusion of independent variables that were computed to be statistically insignificant. Regression diagnostics were used to scrutinise resultant regression statistics for linearity, normality, homogeneity, collinearity and singularity.

3.2.7 Study 6: Fault Detection in Refrigeration Systems

Study 6 looked at the operational data of commercial refrigeration systems aiming to gain insights about the operational behaviour of the systems. For the purpose of this study a mixture of methods (non-linear regression, Fourier transforms, etc.) was used in order to deal with the complexity of the objective.

For this study, stores were selected using the selection criteria below:

- Electricity data had to be available for each pack between 1/11/2012 and 1/11/2013.

[1] Shapiro-Wilk test non-significant

- System operation data (such us suction pressure and evaporator temperatures) had to be available for the same time period to match the electricity data.
- Stores had to have been fitted with an 'Einstein E2' front panel controller; this controller provided the most comprehensive operational data out of all the installed controllers in the estate of the organization.
- Selected stores all use the same refrigerant, R404A, to keep the system configuration as similar as possible.

Measurements of all variables were compiled for each store. For a complete list of data available, and a description of the refrigeration system please look at Appendix C. Subsequent analysis was carried out in Interactive Data Language (IDL) [48]; IDL is an interactive data language that allows the user to analyse complex data and create meaningful visualisations. The dataset was checked for quality and completeness; where missing values were observed in the weather dataset (less than 10%), these were linearly interpolated. Standardised procedures were not used in this study to exclude outliers; outliers were of interest and therefore needed to be retained. Electricity data was aggregated to hourly intervals to match the weather data frequency interval. It was expected that the electricity consumption of the refrigeration packs would be dependent on ambient temperature [49]. For this reason a regression model was built for each pack based on the ambient temperature profile for that region. This regression model simulates the electricity consumption of the pack based only on weather, in the form:

$$Y = Const + W \tag{3.1}$$

where,

$$W = aT + bT^2 + cT^3 \tag{3.2}$$

Y is the predicted consumption for the pack, Const is the constant term in the equation (assumed to be consumption not affected by weather), W is taken to be the effect of weather on the pack. T is ambient temperature, a, b and c are the coefficients for T for each pack. In order to remove the effect of ambient temperature from the dataset, W was subtracted from the actual consumption, E, of the store.

Removing the effect of ambient temperature on the consumption of the system (W) makes the identification of faults easier as it removes the skewness inflicted by an external factor. Based on what is known about the operation of the refrigeration packs, it was expected that the electricity demand would have some periodic patterns. For example, defrost cycles [2] (scheduled

[2] In commercial refrigeration systems ice build-up on the evaporator is a common problem, in order to avoid that, some systems are scheduled to 'power down' for a few minutes allowing for this ice built up to melt

to be carried out at specific time intervals depending on the type of case), time of day, and day of the week. For this reason the electricity data, after the effect of weather was removed, was transformed into the frequency domain using the Fast Fourier Transform (FFT) function in IDL [48],[50]. The FFT function converts data into the frequency domain, while the inverse FFT function converts data back into the time domain, as shown in Figure 3.2.

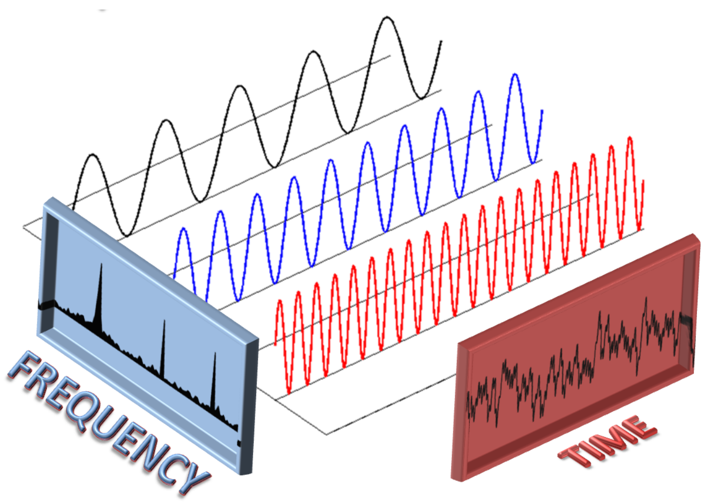

Figure 3.2: Fourier Transform explanation. Image from [51].

The results showed that some frequencies have much higher amplitude than the rest, indicating that there are events that happen periodically with that frequency (see figure 4.34). For example defrost cycles that happen three times a day were represented by a spike at eight hours. Similarly a spike at seven days represented the weekly operation of the store, and the variations in opening hours between weekdays and weekends. The FFT also highlighted that there were other periodic events in some stores that required further investigation.

Following standard digital signal processing principles, the dataset was cleaned by removing the peaks representing the periodic events caused by known factors. These were: the four/six/eight-hourly peaks depending on the defrost settings of the pack, the 24-hour peak, and the seven-day peak. The 'zero' or DC peak was not removed because the removal of this peak results in the exclusion of all noise from the original signal; the faults of interest to this study would fall under the 'noise' category as they are expected to appear randomly in the dataset. After the removal of the peaks, an inverse FFT was used to transform the data back into the time domain. For more information about FFT and signal processing see [50] and [52].

As the focus of this study was to identify incidents that cause an increase in energy, any outlier data points needed to be investigated. In order to do so, the mean and standard deviation of each electricity dataset was calculated, and any data points that fell outside two standard deviations from the mean were selected for further investigation.

The aforementioned methods for Study 6 (and 7) are summarised in Figure 3.3.

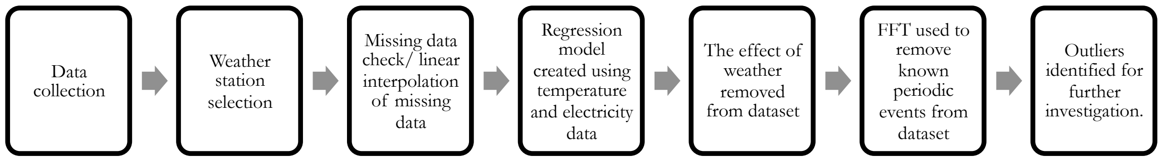

Figure 3.3: Summary of methodology for Studies 6 and 7

3.2.8 Study 7: Validation of the Fault Detection Method

Study 7 was designed with the aim of validating the method adopted for Study 6. Out of a random selection of twenty stores, five were selected for analysis as they had electricity data available for 12 months starting on the 1st of October 2013. A further store was selected because it had missing data at the beginning of the period, as it was important that the method was tested when there were missing data.

The method developed for Study 6, and presented in Section 3.2.7, was used for this Study 7. Following that the outlier periods in consumption were investigated further using the operational data for the packs, from Database 2, Figure 4.1.

3.3 Summary

This chapter has provided the overarching methodology of this work as well as a description of the methods used in each study. It has explained that an action research methodology was used throughout this work because of the nature of the project and its focus on the industrial sponsor. Furthermore it has introduced the methods used for each study which started from exploratory research methods and ended by creating a new method for analysing and interrogating minute-by-minute data from refrigeration systems. The studies undertaken to meet each objective, along with the deliverables produced, are shown in Figure 1.2.

Chapter 4: The Research Undertaken

The aim of this project is to understand the energy consumption of the retail buildings which make up the Tesco estate, calculate best practice and find ways to identify opportunities for energy reduction. The specific objectives have been detailed in section 1.2. This chapter details the work undertaken for each of the aforementioned objectives and each study (numbered 1-7 in Figure 1.2) is discussed in detail. Study 1 was carried out to address Objective 1, Studies 2 - 4 address Objective 2, Study 5 addresses Objective 3, and Studies 6 and 7 address Objective 4.

4.1 Study 1: Data Available to this Research Project

This research project was heavily dependent on the available data within the sponsoring organisation. As such, this first study addresses Objective 1 of the project by collecting and reviewing all the available information. It aims to gather information about the different store types and the electricity and gas demand drivers, and assess the robustness and applicability of the data within the research scope of this project. The databases available to this research project are summarised in Figure 4.1.

4.1.1 Building Types

The organisation's retail building stock studied here is comprised of four different store formats, which can be aligned with the common categories based on sales floor areas as shown in Table 4.1 [53]. Whilst there is a high degree of heterogeneity across the store categories, this reduces when inspecting the stock within each category. Store formats differ in terms of size and location, as well as different products and on-site offers. The sections below give a more detailed description of each category.

Convenience stores (Express) are the most common category of stores in the organisation's stock, numbering more than 2,000 (more than 50% of the total stock) [54]. They are usually found close to the consumer; either located within a town centre, close to apartment

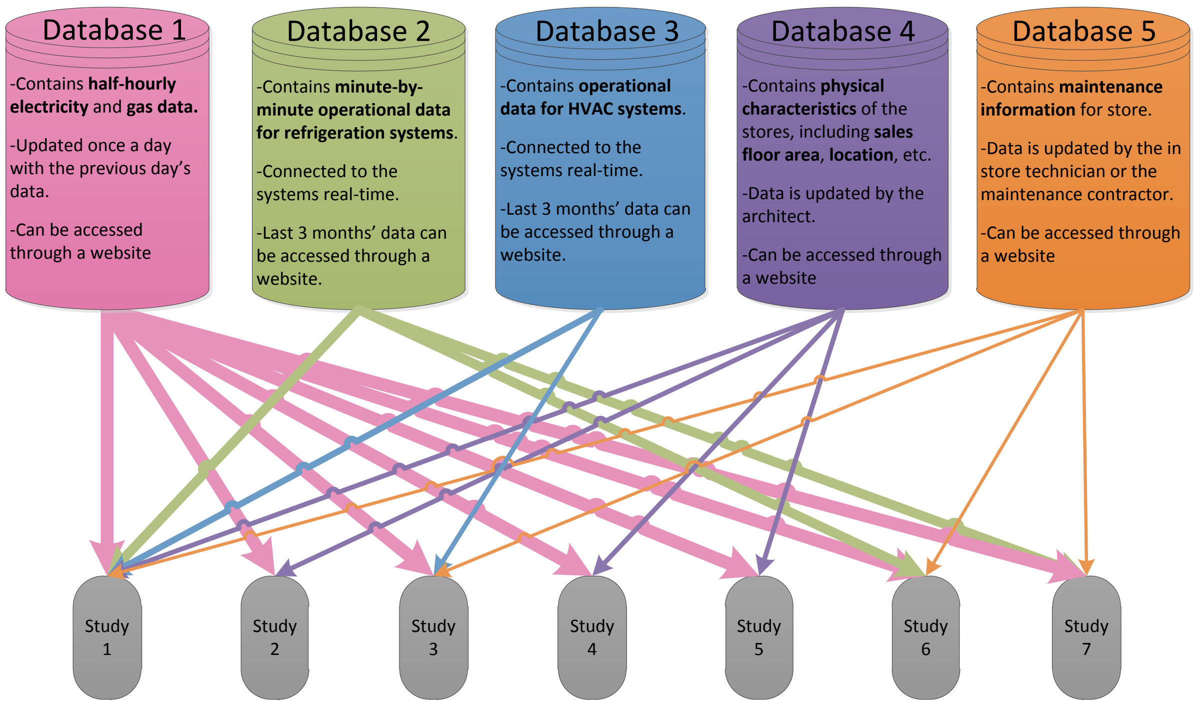

Figure 4.1: Databases used in this work

Category	Sales floor area [m^2]
Convenience store	$<$280
Supermarket	280 – 1,400
Superstore	1,400 – 5,750
Hypermarket	$>$5,750

Table 4.1: Retail store categories from [53]

blocks, or as part of petrol filling stations. Their product ranges, and thereby also in-store services, depend on the local market demand. They are typically closely related to their location in urban centres and are mostly chilled-food dominated as they bring the classic lunch meal to their customers. These stores use electricity for both heating and cooling.

Supermarkets (Metros) are the most individual store category. These stores are usually found within town centres and the building types vary from new, purpose built stores to refurbished buildings such as churches. Similar to superstores these stores include a mixture of in-store services, depending on their location and market demands. Typically they have an in-store bakery but not any fish, meat or delicatessen counters and are a mixture of gas and electrical heating with some having a small number (i.e. one or two) ceiling mounted, cassette type cold air recirculating units for local cooling.

Superstores are the second most common store category, and are found closer to the consumer, usually at the edge of the town centre, and are typically built for purpose. In rare cases some of these stores were acquired from previous owners and refurbished to meet the organisation's design standards. These stores include a mixture of in-store and on-site services, as well as a mixture of construction types, as they can be timber framed, or simple steel framed retail sheds. The majority of these stores are heated by a central gas fired Low Temperature Hot Water (LTHW) system, and approximately 15% of them have a CHP plant that generates electricity and heat. Cooling is provided by centralised constant volume air conditioning systems.

Hypermarkets (Extras) are the largest retail stores within the studied stock. These are usually located outside town centres -normally at the edge of the town- and are designed for purpose, thereby maintaining the organisation's and national building standards at the time of construction. Being the largest stores of the stock, they contain the full range of in-store and on-site services, such as petrol filling station, in-store bakery, fish; meat and delicatessen counters as well as significant non-food sales area, including clothing departments and electronics departments. Although all hypermarkets have similar product lines, the proportional composition of these varies. In general, these stores have similar on-site electrical and gas end-uses. Approximately 75% of all hypermarkets are open 24 hours a day. Similar to supermarkets, the majority of these stores are heated by a central gas fired LTHW system with 15% having a CHP plant that generates electricity and heat. Cooling is provided by centralised constant volume air conditioning systems with vapour compression chillers.

4.1.2 Metering and Monitoring

Data availability was very important to this project, therefore time was devoted at the initial stages of the project to understand what forms of metering and monitoring were installed in the study sample before the beginning of this project. The sections below describe the different types of metering and monitoring in more detail.

4.1.2.1 Electricity Metering

The building energy metering strategy used in the study sample has been created following CIBSE's TM39: Building Energy Metering [55]. As shown in Figures 4.2 and 4.3 the main incomer of each store is metered via a meter integral to the Air Circuit Breakers (ACB).

Stores built before 2010

Submetering was firstly introduced in the estate in 2006 as a capital project, but it was not an integral part of the electrical design until 2010. Thus, sub-metering was retro-fitted to the older stores. Figure 4.2 includes a schematic showing the sub-metering in these stores. This retro-fitted metering has some disadvantages compared to the integral metering that is designed into new stores. One of which is simply that the electrical design of the stores was carried out without metering in-mind, and therefore similar load types were not grouped together. Similarly, circuits were not labelled with metering in mind, which proved to be difficult for the electricians retro-fitting the meters. Additionally, there was no governance process in place for newly added or removed equipment to a store, therefore retro-fitted metering degraded in the years after its installation. What this means is that in stores built before 2008 one can not be sure that all of the equipment that would fall in the above categories is metered. The different loads can appear to be lower than in newer stores, but this can simply be because the whole load is not metered, and not because the specific store is more efficient.

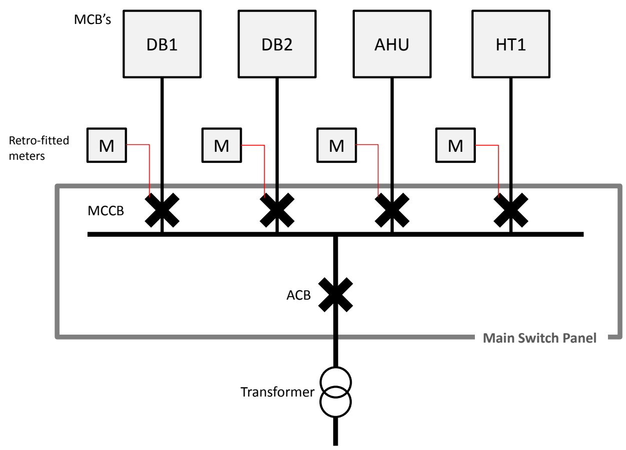

Figure 4.2: Schematic of metering in stores built before 2010

Stores built after 2010

After 2010, when submetering became a design-standard for new stores, the quality of the submetering was improved in the larger stores. One of the reasons is that during the electrical design of each store similar loads were grouped in Distribution Boards (DBs) and then a type was assigned to each one, and they are metered with meters integral to the Moulded Case Circuit Breakers (MCCB). At this sub-metering level, the seven possible options are:

(1) Refrigeration The commercial refrigeration system referred to in this work can be divided into two main parts (Figure 4.4)

- The Pack, which is made up of the compressors and the condensers, and it is located away from the sales floor area, usually found on the roof of the building.

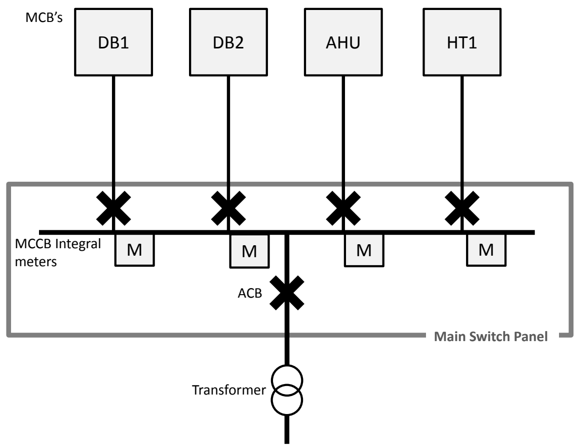

Figure 4.3: Schematic of metering in stores built after 2010

- The Cases, which is a selection of cold rooms and shop floor display cases, with the evaporator element built into each one.

Each refrigeration pack is powered by a separate feed which is metered at the circuit breaker. In most recently built stores a dedicated distribution board is also used for the refrigerated cases on the shop floor.

(2) HVAC Similar to refrigeration packs, each air handling unit and air curtain is powered (and metered) by a separate feed. The heating in the stores is provided by gas boilers, therefore the electricity load for HVAC mainly includes the electricity used for fans, and the electricity used for cooling. Offices at the back of house sometimes have split units installed for heating and cooling. These are small loads and powered by a local DB, so they would not be included as part of the HVAC category.

(3) Lighting The category of lighting does not only include a single item, but a collection of various items in the case of retail buildings. This includes sales floor lighting, carpark lighting, specialist accent lighting and many others. It is anticipated that all lighting related feeds are grouped together and powered by the same (or few) distribution boards, but is not always easily achieved. For example main sales floor lighting might be fed from one DB close to the sales floor, while other lighting, such as back of house or carpark could be fed from other DBs. This introduces some uncertainty into the 'Lighting' sub-meter as these DBs could be powering other functions of the store, such us the cashier desks, sockets on the shop floor or other back of house loads.

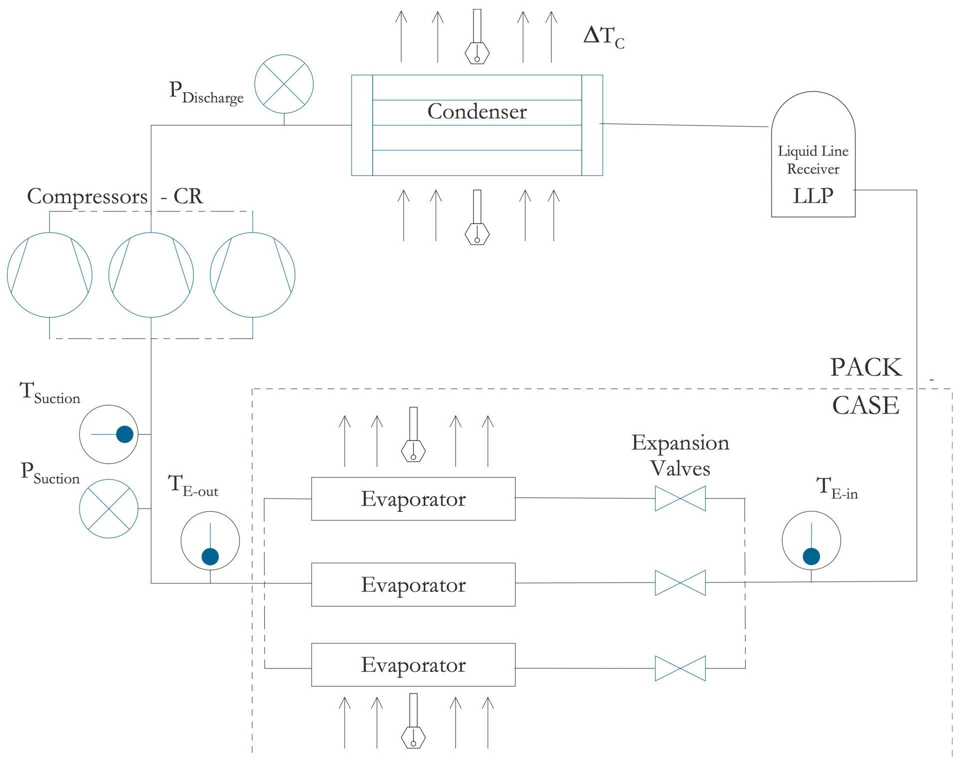

Figure 4.4: Refrigeration system diagram demonstrating the pack and case sides, with available instrumentation (data collection points).

(4) Others This is a category that can be easily misunderstood, hence it has recently been split into three different categories; bakery, hot-chicken and café. It is usually used as a 'summation' category for bakery and hot chicken ovens, as well as the in-store café and the back of house DBs.

(5) Petrol Filling Station (PFS) This category is only used when the PFS of a larger store does not have it's own main incomer and it is fed through the main store. PFS are usually treated as Express (Convenience) and therefore not sub-metered any further.

(6) Low and Zero Carbon technologies Low and Zero Carbon technologies are often included in retail outlets. These might include solar panels, CHP engines, etc. This feed includes both the power usage and the power produced by the technology as separate datasets.

(7) Unmetered Unmetered is not a category as such. It is the difference between the main incomer reading and the summation of all the other sub-meters. In the case of new stores, this value should be very minimal, as it would only include the power consumed by the various alarms and emergency lights which are not metered. In the case of stores built before 2010, this category can be notably larger as explained earlier.

4.1.2.2 Gas Metering

Gas in a retail outlet is mainly used for heating and specialist in-store services such as bakeries and cooking facilities, but the percentage contribution of each end-use is not clear, as gas consumption is not sub-metered. The main gas incomer is fitted with a meter, and if the store has a CHP engine installed, the gas supply to the CHP is also metered.

4.1.2.3 Operational Data

Operational data include information about the operation of various parts of the stores. For example refrigerated case temperatures, in-store temperatures, store opening hours, volume sales etc.

Refrigeration operational data Various sensors are used for the operation of commercial refrigeration systems, including temperature sensors in the cases, compressor run times, suction and discharge pressure. These sensors are monitored remotely through the in-store internet connection and data is recorded every 1-5 minutes on Database 2, Figure 4.1. Table 4.1.2 includes a summary of all the data and their measurement units.

HVAC operational data Similar to the refrigeration systems, HVAC systems require various sensors for their operation. For example each store has an average of five in store temperature sensors. These sensors are again monitored and recorded remotely in an online database (Database 3, Figure 4.1). Due to the fact that data is stored for the last three months at any given time, along with some identified calibration issues (i.e. reading of temperatures as high as 45 degrees Celsius in the winter), this dataset has not been used in this research project.

Sales data Sales data is monitored and recorded from every cash desk in each store and was made available to this project as the weekly total for each store. Sales data was included as a proxy for occupancy data as this was not available. It was considered to be a suitable proxy as usually a larger basket size indicates customers spending longer in a store.

4.1.2.4 Physical and Regional Data

Physical and regional data, such as location and size of the store were available through Database 4, Figure 4.1. This includes more detailed information, such as opening hours, percentage of product mix, number of carpark spaces and exact latitude and longitude position of each store.

Symbol [Units]	Description	Frequency Interval
E [kWh]	Electricity readings from the distribution board servicing each pack (Database 1)	Half Hourly
T [°C]	Ambient Temperature from the nearest available weather station to the store (UK Meteorological Office)	Hourly
MSI	Maintenance and Service Information data- Collected from the maintenance logbooks (Database 5)	Time of addition
$T_{Suction}$ [°C]	Temperature of gas refrigerant before it reaches the compressor (Database 2)	Minutes
$P_{Suction}$ [bar]	Pressure of gas refrigerant before it reaches the compressor (Database 2)	Minutes
$P_{S-setpoint}$ [bar]	Target pressure for the refrigerant before it reaches the compressor (Database 2)	Minutes
$P_{Discharge}$ [bar]	Pressure of refrigerant before it reaches the condensers (Database 2)	Minutes
CR	Indication of the compressor running or not (Database 2)	Minutes
LLP [%]	Percentage of liquid in the receiver (only available if the receiver was fitted with an ultrasound reader) (Database 2)	Minutes
T_C [°C]	Temperature difference of refrigerant before and after the condenser (Database 2)	Minutes
T_{Ein} [°C]	Evaporator air in temperature, averaged across all cases (Database 2)	Minutes
T_{Eout} [°C]	Evaporator air out temperature, averaged across all cases (Database 2)	Minutes

Table 4.2: Available data for the analysis in Study 6

Not all of this information was available for each store, therefore depending on the needs of each study, specific data were selected and used when relevant.

4.1.2.5 Weather Data

Weather data was used at various parts of this project. Degree day data was obtained from BizeE [46] as required. Hourly weather data was kindly provided by the UK Meteorological Office [56].

4.1.3 Data Handling

Data Preprocessing

The electricity, gas, and electricity submetering data is recorded via a logger (data concentrator) at 30 minute intervals and is transmitted to Database 1 once a day, Figure 4.1. Once the data is received in the database, initial cleaning and storing of the data takes place by the database manager. At this stage the various meters that are assigned one of the categories mentioned above are summed together to make up the individual categories. Additionally the electricity generated by low or zero carbon technologies is added to the total consumption of the store, and the ‘unmetered’ load for each store is calculated. In the cases where multiple tenants (other shops) are powered by the same main meter, each tenant is metered separately for charging purposes. This value is subtracted from the total electricity/gas consumption of the building before any other calculations are carried out. The recorded data is routinely checked for spikes, lost communication and broken loggers.

Data Extraction and preparation

At the beginning of each study the data requirements were specified and a data extraction plan was put in place. The process/method varied for each type of database. For example Database 1 was accessible via a web browser, while it was necessary to email the relevant stakeholders to retrieve data from Database 2 that was older than 3 months (Figure 4.1).

After the sample was extracted, quality checks were carried out to make sure the right data was collected. Data was usually transformed into the correct format, depending on the software used for the analysis. As mentioned earlier, Section 3.2.5, the samples were always firstly screened graphically [21].

Different strategies were used when dealing with missing data, depending on the type of analysis. Unless otherwise stated, datasets with missing data were excluded from the analysis. Data of stores that had undergone any type of development works (extension or remodelling) within the study periods were also excluded. Data that included technical faults were treated differently depending on the type of study (see Sections 3.2.2 to 3.2.8).

4.1.4 Summary

The sections above have described the data available for this study. This includes the electricity and gas data available, the operational data, as well as the physical and regional descriptive data for each store. Figure 4.1 summarises the available data by database and study.

4.2 Study 2: Current Practices of Energy Modelling in Tesco

As part of the strategic financial planning of the sponsor organisation, an energy budgeting tool is used. This tool forecasts and allocates the budgets into a weekly plan for energy consumption, including gas and electricity. This plan takes into account the increased sales floor area, as well as a the planned percentage reduction in electricity consumption due to energy efficiency projects applied in the existing estate.

4.2.1 Scope and Aims

The purpose of this Study 2 was to document the energy budgeting process of the Tesco Energy team in 2010 and to identify any advantages and disadvantages of it, addressing Objective 1, *Identify and critically assess the literature and current practices in energy consumption analysis and benchmarking*. For the purpose of this study only the electricity plan will be discussed, as it was the one with the most robust data. Additionally the term 'energy budget' is used to imply a target value for electricity consumption, measured in kW. These budgets are created using a bottom up approach. This is explained further in sections 4.2.2 to 4.2.3.

4.2.2 Overview of the Study

The Tesco forecasting model was established in 2008 in order to produce energy budgets for the year ahead. Private communication with James Conlin, Engineering Performance Analyst, Tesco Stores Limited, revealed that the budgeting model uses a specific Tesco grouping of stores -stores are put into different groups according to their net sales area, and geographical position- to produce a different seasonality profile for each group.

Data inputs

The initial inputs of the model include:

- List of stores that will be trading from week 1 in 2010-11.
- Weekly data for electricity consumption since 2003-04.
- Sales Floor Area of the store.

Group seasonality profiles

The budgeting process uses the aforementioned Tesco grouping and produces a different seasonality profile for each group. Initially the list of stores is filtered according to the following criteria:

- Exclude any store with incomplete data, i.e. less than 52 weeks worth of data in any year
- Exclude stores where the variance in electricity consumption between week 1 and week 52 is greater than $\pm$ 5%.

This filtering removes the stores with incomplete data sets, as well as the issue of stores having a high variance in their consumption at the beginning and the end of the year due to energy efficiency projects or development/refurbishment works.

Equation 4.1 is used for the calculation of the average weekly consumption, awc_n. The total annual consumption of the store is calculated, where $c_{(n,w)}$ is the weekly consumption of the store, with n being the store ID and w=(1, 2, 3 ,..., 52) weeks, and then divided by the number of weeks in the year.

$$awc_n = \frac{\sum_{w=1}^{52} c_{n,w}}{52} \tag{4.1}$$

Equation 4.2 represents a calculation for the Weekly Store Profile, $sp_{(n,w)}$. And it is a percentage of how much above or below average the store will be for each of the weeks in the year.

$$sp_{n,w} = \frac{c_{n,w} - awc_n}{awc_n}\text{x}(100) \tag{4.2}$$

Following that, annual seasonal profiles, sdp_m, for all groups are created. These are the average of the store profiles for each group, Equation 4.3, where sd is the number of stores in a group and m=(1, 2, 3, ..., sd).

$$sdp_{m,w} = \frac{\sum_{m=1}^{sd} sp_{m,w}}{sd} \tag{4.3}$$

These profiles are then smoothed a three-week rolling average using Equation 4.4.

$$BAU_{m,w} = \frac{sdp_{m,w}}{\sum_{w=1}^{3} sdp_{m,w}} \tag{4.4}$$

This is now the Business as Usual (BaU) profile for each group; the forecast consumption with out any reductions or additions. An analyst then rechecks the entry and exit points for each group to ensure they are within the tolerance limits ($\pm$ 5% as mentioned earlier).

The Budget

The average electricity consumption for each group, aec_m, is then calculated, using equation 4.5, based on the most recent data; the average consumption for Week 33 to 38.

$$aec_m = \frac{\sum_{w=33}^{38} sdp_{m,w}}{6} \tag{4.5}$$

The budget is then calculated using Equation 4.6. $B_{m,w}$, is the forecast energy consumption for the stores.

$$B_{m,w} = aec_m \times BaU_{m,w} \tag{4.6}$$

Method for stores not yet open or lacking actual data

This method can be applied for stores with no consumption data, either because the information does not appear in the monitoring database or the store has not opened yet. These stores are assigned a benchmark consumption based on a consumption per square foot calculation, $bc_{n,w}$. All Equations from 4.1 to 4.6 are then used to arrive at a budget for these stores. If the floor area is unknown, then an average floor area is used based on the format type.

Final checks

The budgets produced are checked and any outliers (more than $\pm$ 10% from last year's consumption) are rejected and replaced with a value that is closer to last year's consumption. For example if a store's budget for the year ahead is more than 10% different than its last year's consumption for no apparent reason, then this store's budget will be adjusted downwards. These budgets are updated as more data becomes available in the weeks between the beginning and the end of the year. For example if a store is planned to have an extension, the budget is adjusted using the benchmark for the new floor area of the store. In other cases when there is a project affecting the consumption of the store, such as new lighting, the budget will be adjusted to reflect this. This last step provides the percentage reduction due to energy efficiency projects.

4.2.3 Key Outcomes

This model produces an accurate forecast for the total electricity consumption per week for all stores, but it requires a lot of manual manipulation. For 2010-11 this was within 5% of the actual electricity consumption of the stores for all but three weeks. There was an average of $\pm$1% variance from the budget for the whole estate, for 2010-11.

The model is weaker when one attempts to predict the electricity consumption of each store individually. Despite this, the budget for 1752 stores was within 10% of their actual electricity consumption at the end of the year. The results of the model are summarised in table 4.3.

The model presented in this study was initially developed in 2008 and has been continually improved since. This constant review allowed for a better methodology and more accurate

Percentage difference from budget	Number of stores
$\triangle B \geq 25\%$	31
$25\% > \triangle B \geq 10\%$	97
$10\% > \triangle B \geq 5\%$	174
$5\% > \triangle B \geq 0\%$	600
$0\% > \triangle B \geq -5\%$	662
$-5\% > \triangle B \geq -10\%$	316
$-10\% > \triangle B \geq -25\%$	358
$\triangle B < -25\%$	75
Total	2313

Table 4.3: 2010-11 Store budget difference from actual

predictions. It was observed that the energy consumption of the stores is affected by extremes of ambient temperature and can cause the budget to over/under estimate by 30% for a specific week. Nevertheless, this is usually balanced out in the Year-to-Date (YTD) performance.

Advantages and Limitations For Tesco

As with any tool, there are advantages and limitations of this tool for Tesco which are summarised below

Advantages

- The budget is created and edited in house;
- Predicts the total energy consumption of the estate to an accuracy of $\pm 5\%$;
- Does not need accurate weather forecasts as the weather is not part of the model; and
- It can be edited to reflect recent changes in the estate, including projects and acute weather.

Limitations

- It is time consuming to create the budget and proof read it;
- Inaccuracies exist at store level, high weekly discrepancies between model and actual;
- It does not take future weather into account;
- When editions are needed, it is time consuming to make these changes;
- It does not use all the available data; and
- It does not identify efficient and inefficient stores.

Technical Advantages and Limitations

This tool is a tailor-made solution for Tesco, and while this works for the company, it does not take advantage of the knowledge of other models.

Advantages

- It is based on historical data;
- It takes into account some of the factors that affect the energy consumption;
- It allows for fluctuations; and
- It is not based on 'inaccurate' weather information.

Limitations

- It does not take into account all of the factors that affect energy consumption;
- It is not based on strong statistical analysis;
- No correlation analysis/ multivariate regression was carried out before the original development;
- It is time consuming to develop (analysts work on it for over two months each year); and
- It does not take advantage of specialist statistical packages.
- It does not indicate whether a store is efficient or not.

Proposed improvements

Following the advantages and limitations summarised earlier, this section suggests areas for improvement, along with the proposed solutions.

1. The current method creates group seasonality profiles but there is no proof that the stores comprising each group are similar to each other or have the same seasonality profile. It is suggested that stores with a similar seasonality profile are grouped together, rather than following the Tesco grouping.

2. Current benchmark values only take the square footage of the store into account. More accurate and sophisticated benchmarks can be created that take into account more characteristics of the store, such as sales.

3. All the work is being carried out in MS EXCEL. A more sophisticated tool can be used to automate the process and make it quicker.

4. Weather data is not taken into account. Weather data can be used to inform the process. For example in Equation 4.2, there could be a second term that calculates the percentage difference in energy consumption according to degree days.

5. Level of detail. The current tool provides a budget for the main electricity and gas consumption of the stores, but not for the individual store areas. Weekly budgets for each store area could be produced, which would also help the team identify exceptions easier.

4.2.4 Summary

Study 2 presented the background of the Tesco Energy budgeting model, including the need for it, and the data availability during its development. The modelling tool used for the creation of weekly energy consumption budgets for each store was thoroughly discussed, including all equations and assumptions used, as well as deviations from the model when data availability was low.

Even though the model was considered as adequate for the needs of the team and it did serve its purpose for the business, its advantages and limitations were summarised, providing the foundation of the prediction tool discussed in Study 5, Section 4.5.

4.3 Study 3: Analysis of the Electricity Consumption of two Supermarkets

As stated earlier, Tesco has pledged to reduce the carbon footprint (per square metre) of its buildings by 50% by 2020, based on a 2006 benchmark. In order to do so, a programme of ‘energy efficiency projects’ was set in place in the same year. Study 3 uses a case study method to understand the effect of these projects in the electricity consumption of two stores.

4.3.1 Scope and Aims

The scope of this study was to investigate the effect of the energy efficiency projects on the electricity consumption of stores built in 2006. Two superstores were selected, located in different parts of the country. Even though all stores had electricity meters installed when built, sub-metering was not installed in these stores until 2008. The aim of this work was to identify potential drivers of electricity demand, and understand which specific sub-meter they affect, Objective 2, *Analyse existing energy consumption data for the Tesco estate and establish correlations with possible drivers (such as weather, time of year, sales etc.)*.

4.3.2 Overview of the Study

Two stores were investigated as part of this study. Electricity and project data were collected for each of them. Initially weekly electricity data was plotted against project installation dates. Each peak and trough of the consumption was then investigated. This included cross referencing with project information data, as well as more detailed interrogation of the electricity data, down to the half hourly level. The following section includes a summary of the key outcomes/learnings from these case studies.

4.3.3 Key Outcomes

Overall electricity consumption

One of the first things observed during the analysis of the data from both of the stores was that the overall electricity consumption had a downward curve for all the years of the monitored data, until there was a refurbishment project. Further investigation has indicated that the overall consumption of stores was constantly improved, either due to the installation of energy efficiency projects, or due to operational changes. The increase observed during the refurbishment project can be explained by the installation of more equipment in the stores, i.e. more bakery ovens or more accent lighting.

Data from both stores are shown in Figures 4.5 and 4.6 where one can observe the downward energy consumption (black line) across the years [1], with an increase around the red vertical line, which indicated the refurbishment project. The grey lines indicate the installation dates of other energy efficiency projects. The following sections describe the effect of some of these projects in relation to the specific sub-meter they affected.

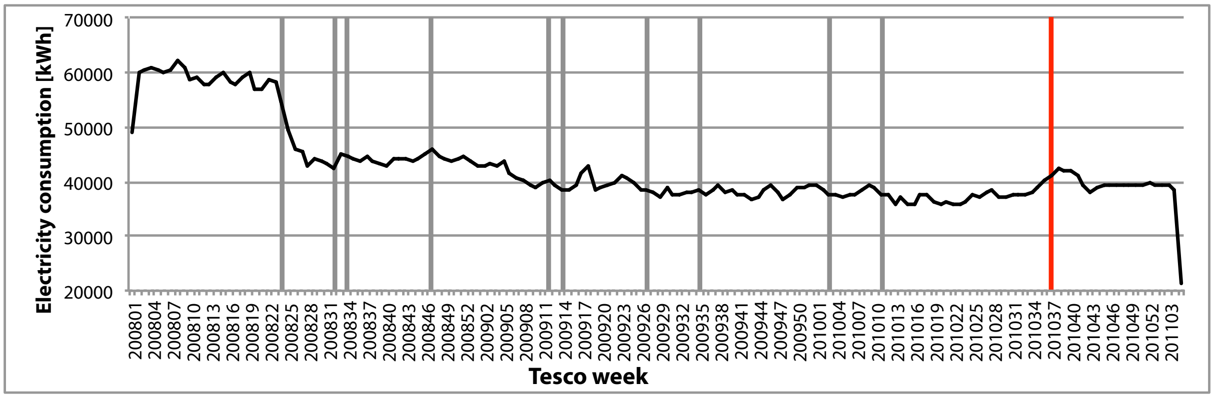

Figure 4.5: Total electricity consumption of store 1 for the past 3 years, with lines indicating the installation dates of energy efficiency projects

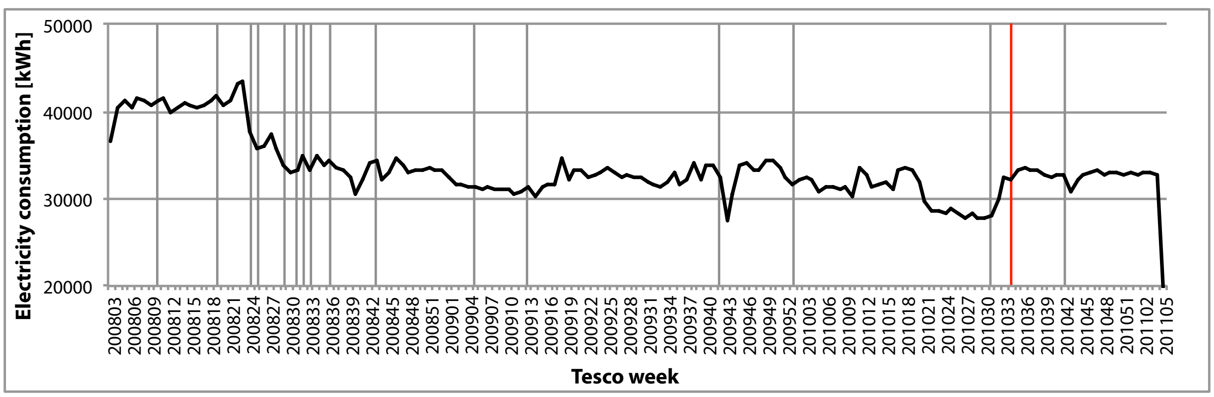

Figure 4.6: Total electricity consumption of store 2 for the past 3 years, with lines indicating the installation dates of energy efficiency projects

Lighting

The lighting profile of store 1 is presented in Figure 4.7. Consumption was found to be relatively constant unless a project was carried out. It was noted that in the first few weeks of 2008 the consumption was higher than expected, spiking at week 8 of 2008. In order to understand what

[1] Tesco Week indicates Tesco's financial year, which usually runs from March to March

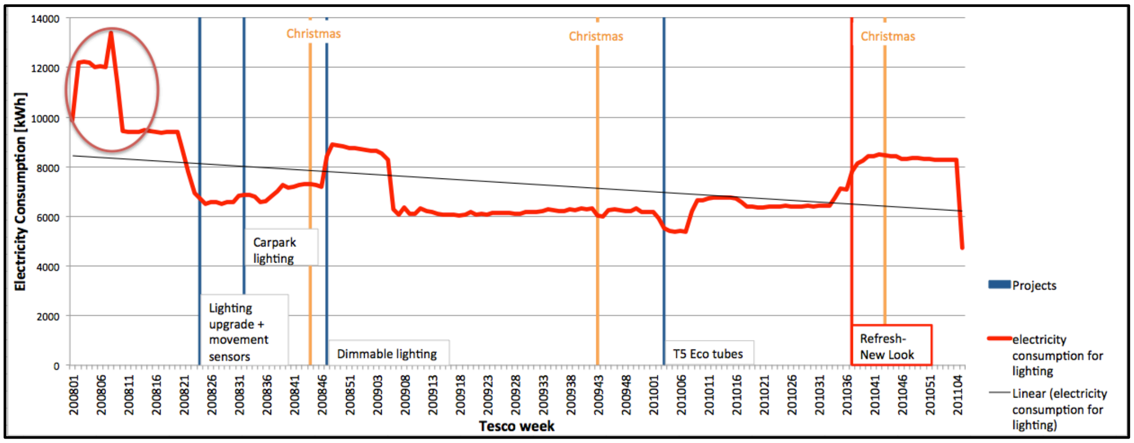

Figure 4.7: Electricity consumption for lighting of store 1

went on during that period, the actual half hourly meter readings were explored, Figure 4.8 shows the readings from one of the meters.

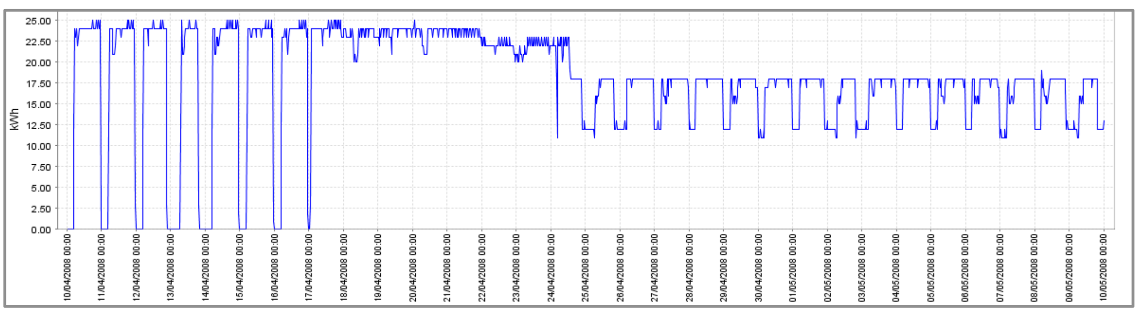

Figure 4.8: The lighting half hourly meter showing that none of the lights were being switched off in store 1 in week 8, 2008

Figure 4.8 indicates that during week 8 (18-24/4/2008) none of the lights were being switched off. This was resolved in week 10, probably by connecting the lighting to the automatic switching system. In the new pattern, one can identify the Sundays (for example 2/5/2008), which have less trading hours, requiring the lights to remain on for fewer hours. It should also be noted that not all of the lights switch off, this is because the store is open 24hours a day, therefore lighting reduces to approximately two thirds of the original lux levels for night-time trading. Another spike in consumption was observed after the installation of dimmable lighting (Week 47 in 2008). As indicated by Figure 4.9 this resulted to more lighting being switched on and off, which was not repaired until 3 months later. This might be due to wrong commissioning from the contractor that resulted to increased lux levels in the store. When this was identified, lux levels were lowered, reducing the electricity consumption to a level lower than before the installation of the dimmable lighting.

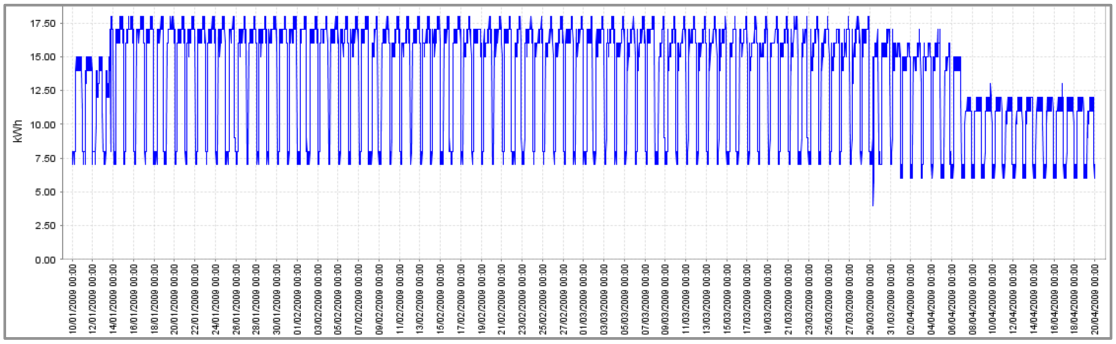

Figure 4.9: The lighting half hourly meter showing that more lighting was being switched on and off in store 1 after the dimmable lighting was installed.

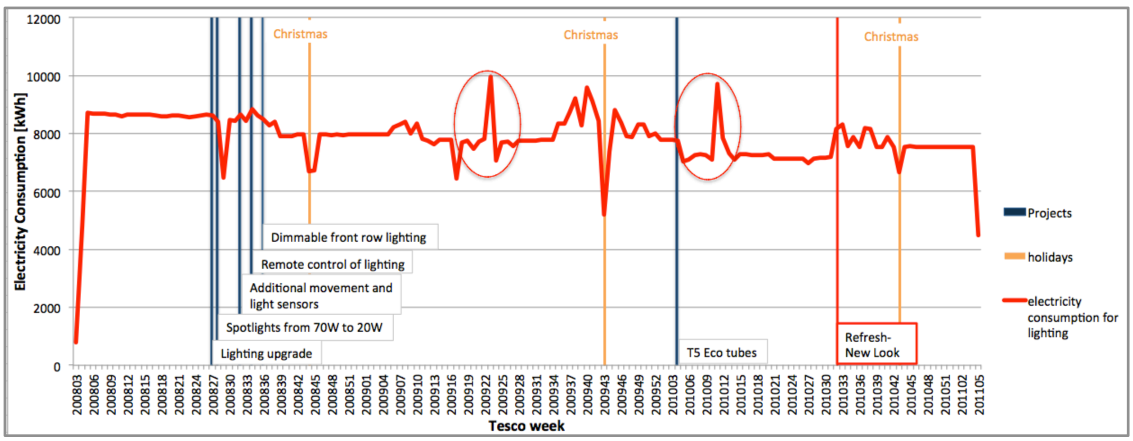

Figure 4.10: Electricity consumption for Lighting of store 2

Two spikes were also observed in store 2 (see Figure 4.10), and after further investigation through the half hourly meter (see Figure 4.11) it was found that the lights were left on 24/7 during those weeks.

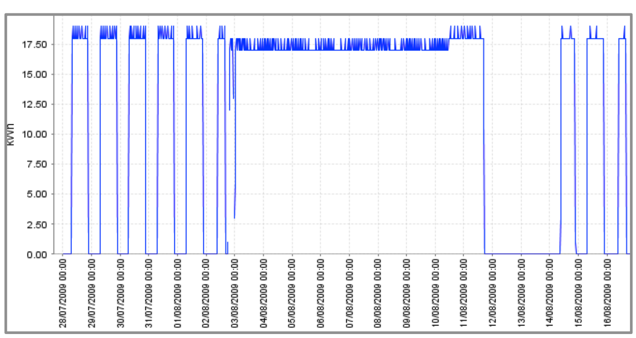

Figure 4.11: The lighting half hourly meter showing that the lights were left on 24/7 in store 2.

Refrigeration

The electricity consumption for refrigeration in store 1 is shown in Figure 4.12. It was observed that the consumption for refrigeration was closely following the weather profile for the same time period in both stores. In week 34 of 2008 the constant power fans in the freezer cases of store 1 were replaced by Electronically Commuted (EC) fans, (Figure 4.12), which caused a decrease in the energy consumption for refrigeration. Around week 27 of 2009, there was an unusual decrease in the consumption of the same store; this can be explained by a 'work order' raised by one of the energy managers. It was found that the refrigeration packs had been working at full speed for some time, and that some of the packs were running low on refrigerant gas. These were fixed in the same week and therefore the electricity consumption was reduced.

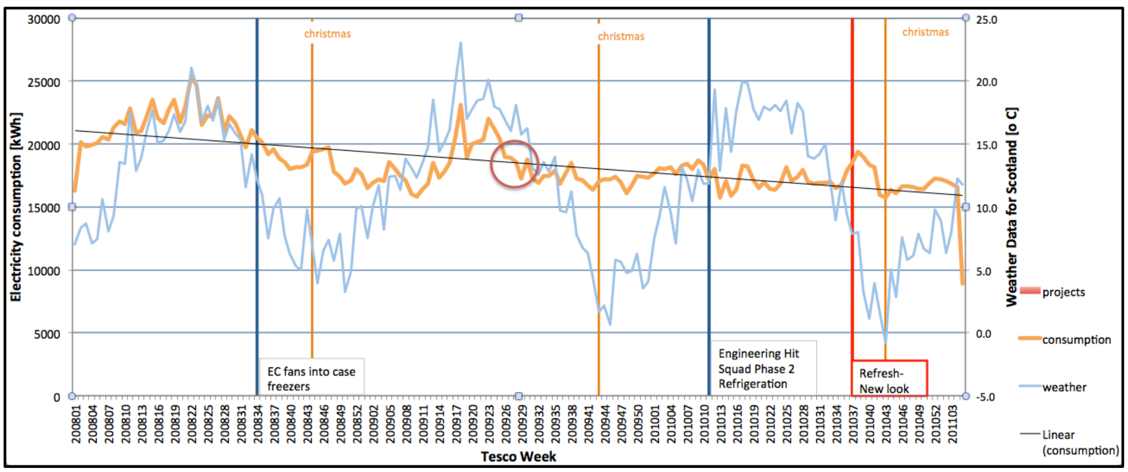

Figure 4.12: Electricity consumption for Refrigeration of store 1

HVAC

One would expect the HVAC consumption of retail stores to be weather dependent, as the majority of buildings, but data from both stores show otherwise. For both stores the consumption was found to be generally constant, unless affected by a project or a fault of the system. This is not typical for buildings, but in the case of retail it can be explained by the fact that in HVAC systems it is mainly the compressors and fans that consume electricity (some of which are not fitted with variable speed drives); heating is provided by gas, and cooling is not always required because of the cold air retrieval system which recirculates cold air from the refrigerated aisles in the rest of the store. Figure 4.13 shows the HVAC consumption of store 1.

Interestingly the large dip in consumption during week 23 in 2008 can only be explained by the over-door heaters being switched off, indicated by the fourth meter in Figure 4.14. The

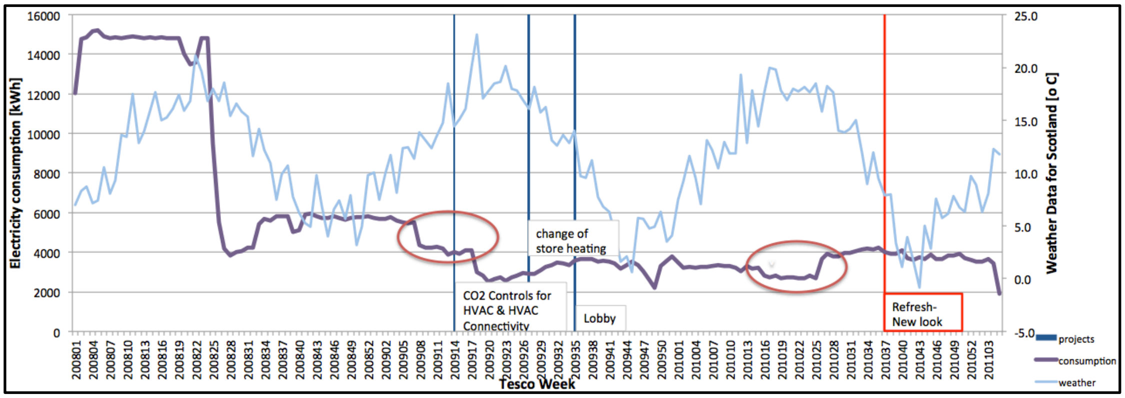

Figure 4.13: Electricity consumption for HVAC of store 1

over-door heaters have been used since, but at different settings that use less energy. The two instances where the consumption rapidly drops and then increases again during the period of one year can be identified using the actual meters in the store, but there is no data indicating what caused these differences. It could be that some packs were not working correctly and were then fixed or replaced without informing the database.

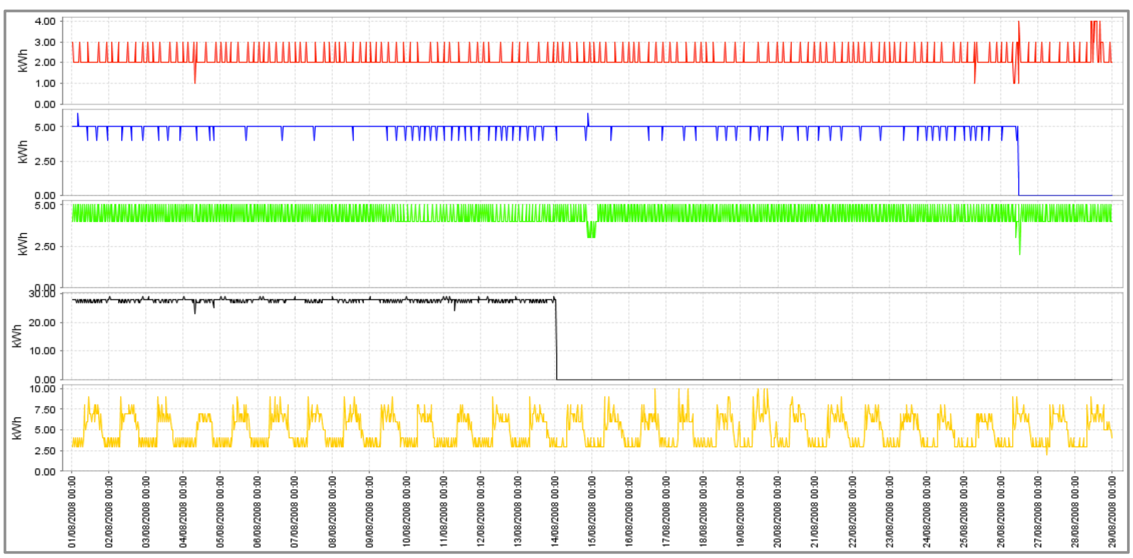

Figure 4.14: HVAC sub-meters in store 1. Systems 1, 2, 3, 4 and 5 are shown.

Others [bakery and hot chicken]

The consumption for others was expected to be constant across the years, as there is a set time for baking in each store. The three dips noticed in the consumption of store 1, Figure 4.15, around Christmas are due to the store being closed on Christmas day. The three peculiar peaks could not be explained initially, but after some investigation it appears that they all fall during the May bank holiday weekend; when it is known there is a higher demand for bakery goods and hot chicken.

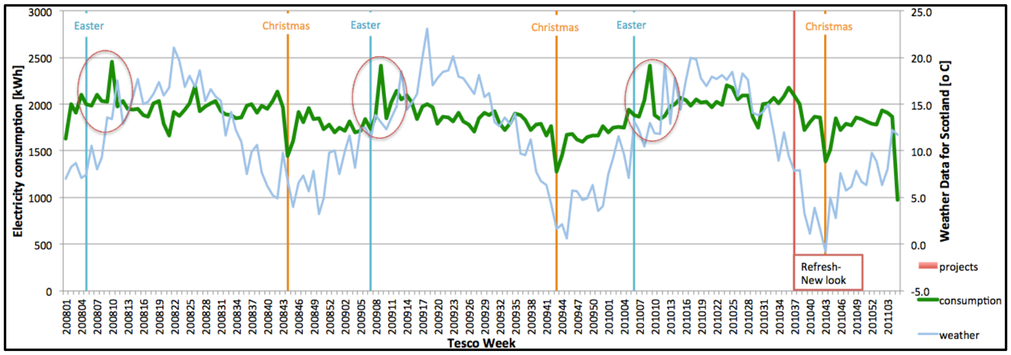

Figure 4.15: Electricity consumption for Others (bakery and hot chicken) of store 1

The consumption of others in store 2 was possibly affected by the two projects installed. In Figure 4.16 one can see the effect of the first two projects quite clearly. The time switch installed in week 34 has decreased the electricity consumption of the ovens. This reduced consumption was maintained until week 14 of 2009 when but new hot chicken cases were installed which increased the consumption to more than twice the original. Figure 4.17 shows that the new cases were used for the same time as the previous ones, but they were either more in quantity or had a higher power rating than the equipment they replaced.

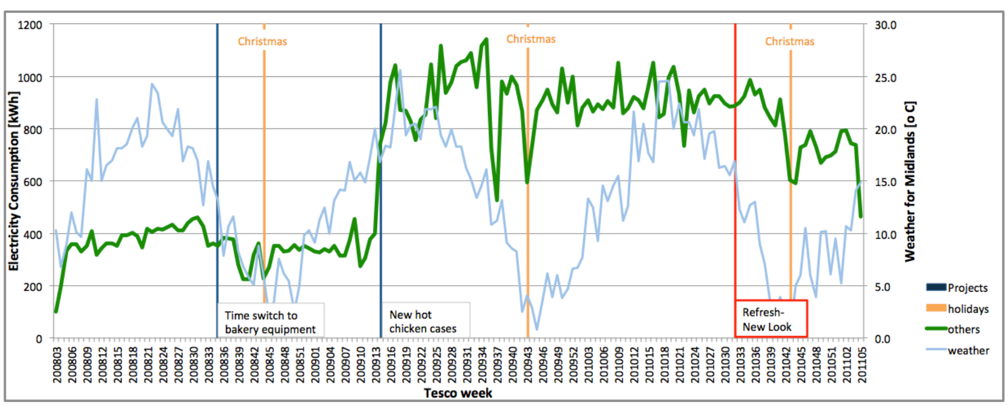

Figure 4.16: Electricity consumption for Others (Bakery and hot chicken) of store 2

Unmetered

The unmetered consumption of both stores was on average reducing over the years, affected by various projects implemented in the stores. The only clearly visible project in the consumption

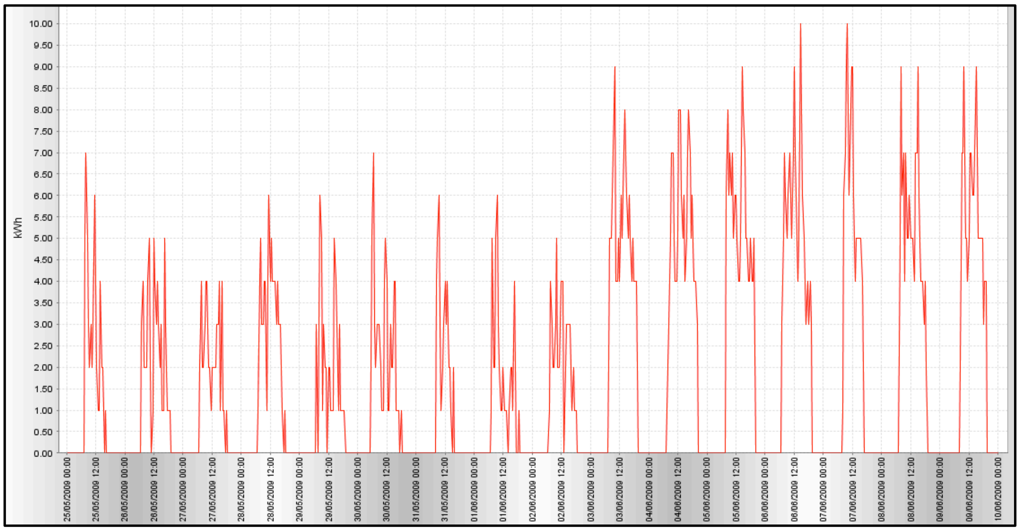

Figure 4.17: The submeter for hot chicken and bakery of store 2

of store 1 (Figure 4.18) is the voltage reduction/optimisation one that resulted in a considerable drop. Similarly the consumption of store 2 (Figure 4.19) was visibly only affected by one project. After further investigation and discussions with the energy managers this was found to be a set-point change of the over door heaters in the store. This change reduced the temperature set point of the heater, which reduced the need for the heater to switch on as often, offering a notable reduction in the unmetered consumption of the store.

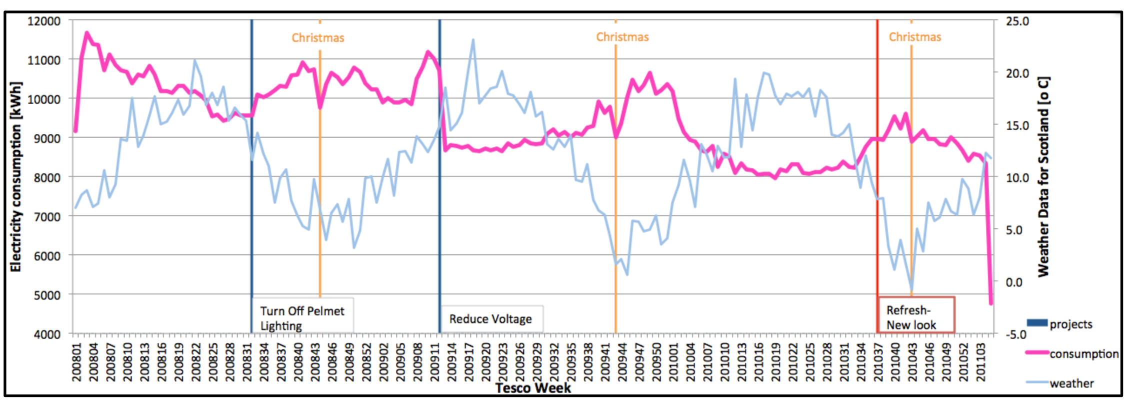

Figure 4.18: Unmetered electricity consumption of store 1

4.3.4 Summary

The findings from two case studies have been presented, showing a reduction of 30% and 40% of electricity use over the course of 5 years across the two stores. The installation of the en-

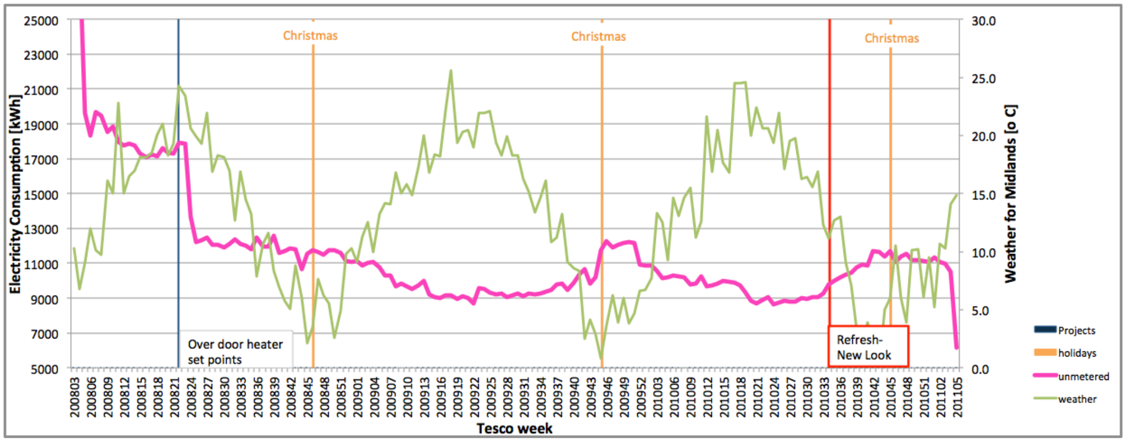

Figure 4.19: Unmetered electricity consumption of store 2

ergy efficiency projects/measures was found to be effective, as energy consumption reductions have been observed; however, there is a concern that the way the projects are currently being delivered and commissioned is not the very effective. For example some lighting projects were carried out in the course of 6 different weeks and adversely affected each other instead of reducing the consumption. It was suggested that the International Performance, Measurement & Verification Protocol (IPMVP) [57] should be used when installing and evaluating energy efficiency projects.

It was identified that an improvement could be made in the delivery and commissioning of these projects by firstly identifying stores that require these projects, and then by delivering these projects as a programme of work, instead of individual projects. As such, the prediction tool discussed in Study 5, Section 4.5 needs to be able to enable the energy managers to identify stores that could benefit from energy efficiency projects.

4.4 Study 4: Analysis of the Available Data for the whole Estate

4.4.1 Scope and Aims

Study 4 was designed to address Objective 2, *Analyse existing energy consumption data for the Tesco estate and establish correlations with possible drivers (such as weather, time of year, sales etc)*, by allowing information gathering and knowledge generation based on the energy consumption data for all of the types of stores in the Tesco estate. The output of this study was presented as a conference paper [1] which can be found in Appendix A and should be read alongside this section.

4.4.2 Overview of the Study

For Study 4, data from Databases 1 and 4 (see Figure 4.1) were collected and analysed in order to understand which factors affect the energy consumption of stores. Data included electricity and gas consumption data, hours of operation, weather information, volume of sales and more. Variables were tested against each other one by one, and for each individual store type; the most interesting/significant results are presented below.

4.4.3 Key Outcomes

Electricity and gas benchmarks

As a first step, the consumption of all stores was divided by the sales floor area (SFA) of the store in order to understand whether there were differences between each store type. Figure 4.20 shows the difference in consumption per square meter for each store type within the Tesco estate. It is apparent that as the store gets smaller, both its electricity and gas consumption per square metre increase. One reason could be that smaller stores (Express and some Metros) are electrically heated. Tassou et. al. [7] also suggest that the balance between refrigerated/frozen and ambient products is an important factor that influences and justifies the higher energy intensity of smaller stores.

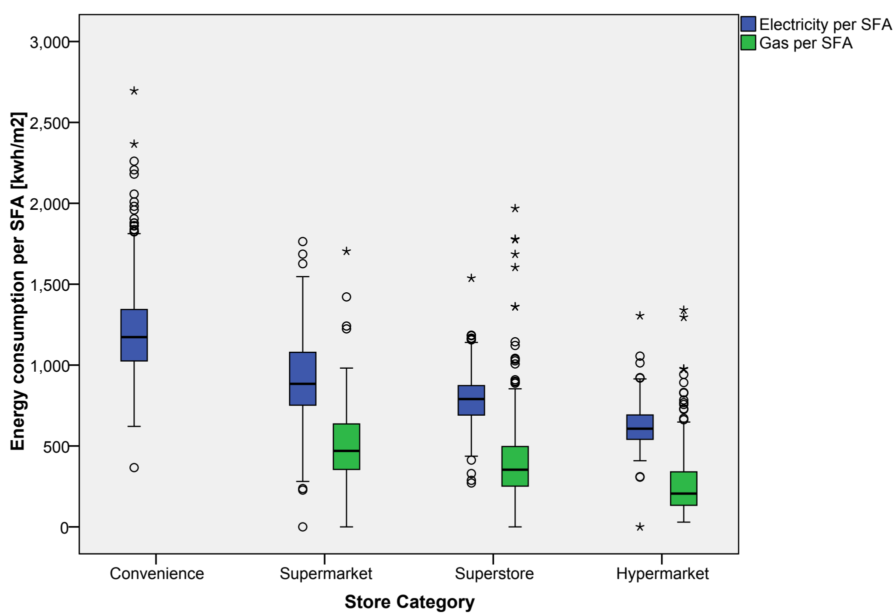

Figure 4.20: Energy Consumption of Buildings in the Tesco estate

Percentage of each submeter

In order to understand the percentage of end-uses of electricity and gas in supermarkets, Figure 4.21 was created. Figure 4.21 presents data for the each store type (excluding Express/convenience as these are not submetered) in stores built before and after 2010. As explained earlier in Section 4.1, stores built before 2010 were retrofitted with submetering while stores built after 2010 were designed and built with submetering integral to each DBs. Figure 4.21 shows that the electricity consumption of refrigeration is the largest end-use electricity demand. Simultaneously it can be noted that the percentage of electricity that is unmetered is quite high. This could cause the submetered data to be unreliable, especially when comparing stores against each other.

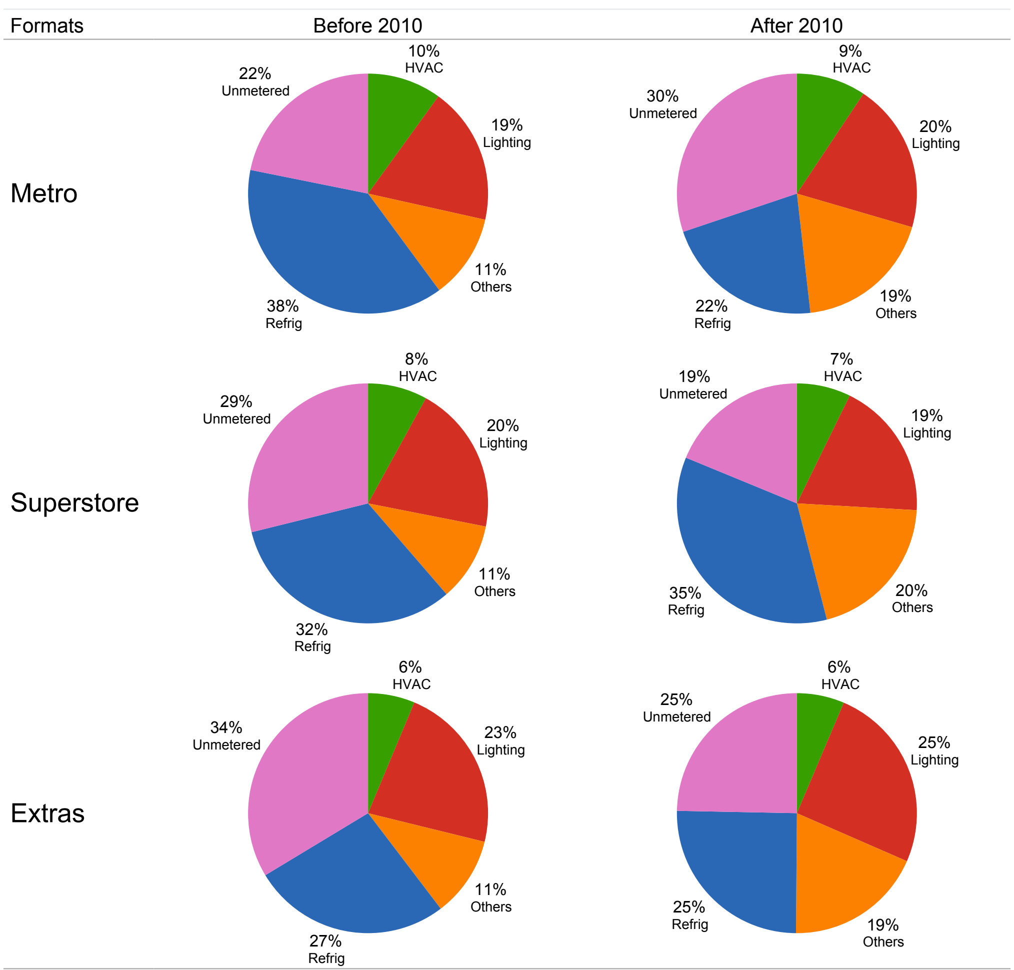

Figure 4.21: Percentage of end uses according to submetering installed.

Impact of weather

It is widely known that outside air temperature affects the energy consumption of buildings. However, each building is different and may behave differently under distinctive circumstances. It was noted that when temperature deviated from the average, the electricity consumption of stores increased. This increase is believed to be due to the heating load during winter (in electrically heated stores) and due to the heavier cooling load and refrigeration during summer. The effect of temperature on gas consumption is obvious when plotting the average weekly energy consumption in kWh against outside air temperature for the same period. Figure 4.22 shows how the gas consumption is affected by outside air temperature.

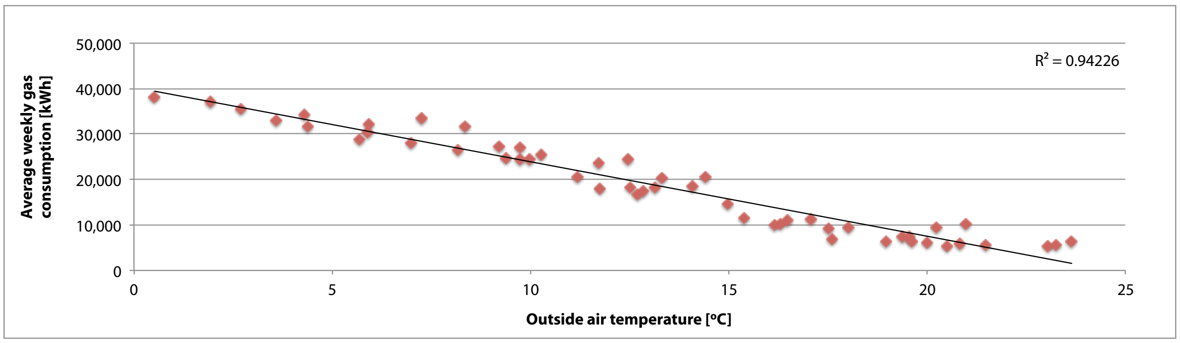

Figure 4.22: Average gas consumption against outside air temperature.

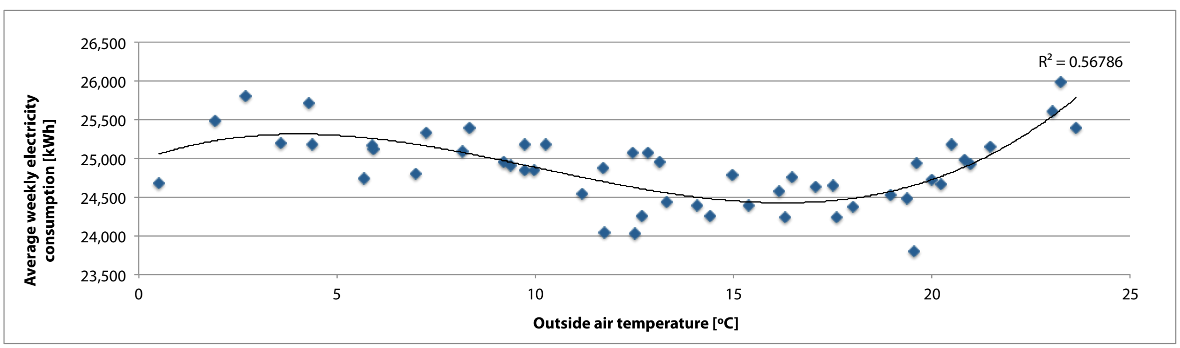

Figure 4.23: Average electricity consumption against outside air temperature.

As shown in Figure 4.23, the electricity consumption of retail stores in the Tesco estate varies with temperature. The heavier electricity consumption during summer can be explained by the cooling load needed but all stores, see Figures 4.24 and 4.25. This consists of the electricity needed to keep the stores cold, as well as the electricity needed for refrigeration. During winter the electricity consumption is again high. This is mainly driven by the heating load of the smaller stores as they are electrically heated, see Figure 4.25.

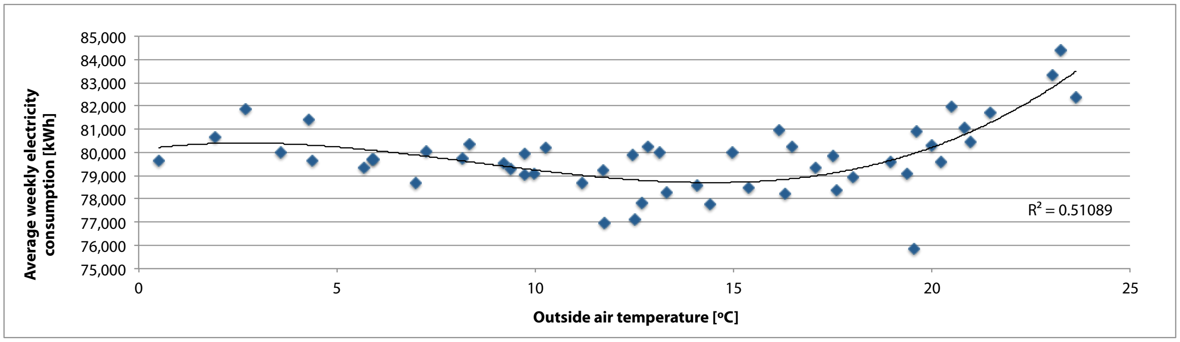

Figure 4.24: Average electricity consumption of Hypermarkets against outside air temperature.

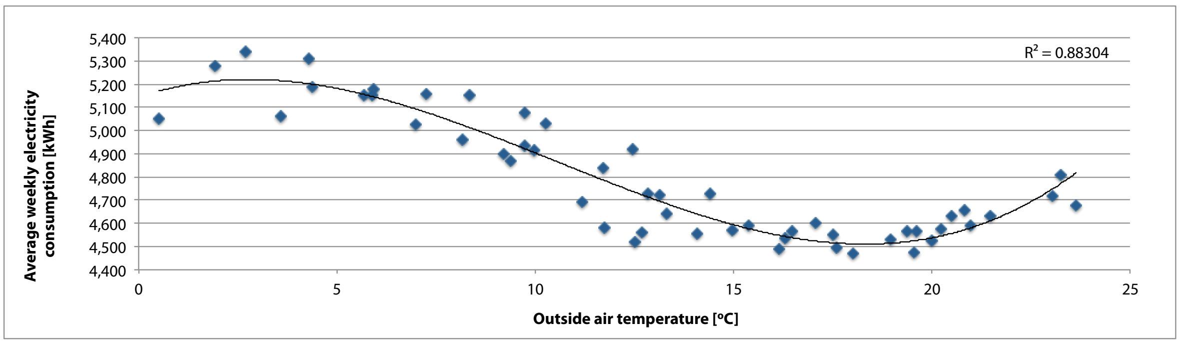

Figure 4.25: Average electricity consumption of Convenience stores against outside air temperature.

Day-of-the-week

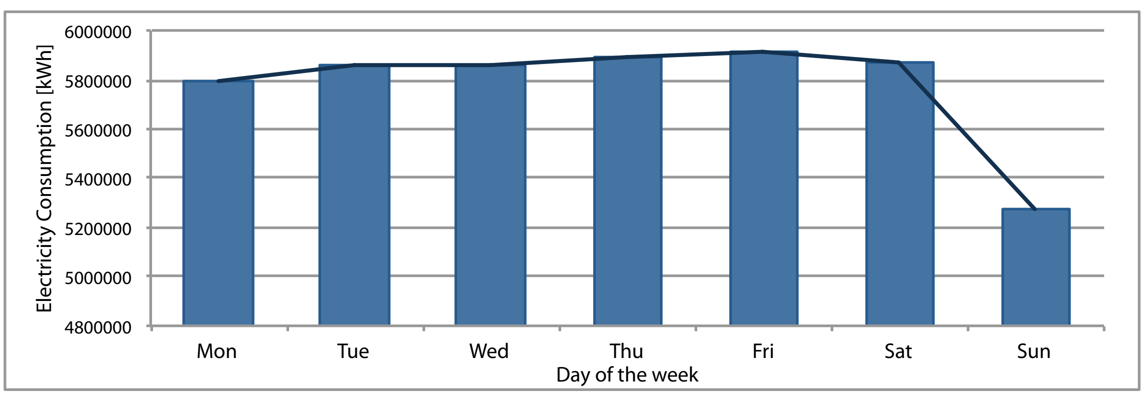

Figure 4.26: The effect of the day of the week on electricity consumption.

Figure 4.26 indicates that the day-of-the-week is an important factor affecting the electricity consumption. It has been observed that on Friday and Saturday stores consume more electricity than the rest of the week, even though trading hours on Tuesday to Friday are the same. This could be explained by the number of customers entering the stores during the weekend and the number of sales/pounds spent in store (usually linked with refrigeration doors opening and closing more often, with customers taking products off the shelves, and staff refilling the shelves), but more information is needed to confirm this.

Sales

Figure 4.27 shows the average weekly electricity consumption of stores against weekly sales; there is a good correlation of consumption with sales (r^2=0.94, p<0.001). However, a closer look reveals less correlation within each store type. This is especially apparent in Express stores as the range in energy intensity is higher than any other store type (r^2=0.23, p<0.001). Figure 4.28 presents the electricity consumption of hypermarkets against sales (r^2=0.57, p<0.001). It is important to notice that stores of the same type, and same size consume different amounts of electricity when their sales volume is different. This could explain why the correlation within each store type is not as strong; consumption depends on the volume of sales as well as on the store SFA. A larger volume of sales indicates more customers entering the store (or customers staying in the store for longer), which has an impact on both the HVAC and the refrigeration loads of the store; more heating/cooling required, as well as a higher refrigeration load because of more products taken out/replaced in refrigerated cases.

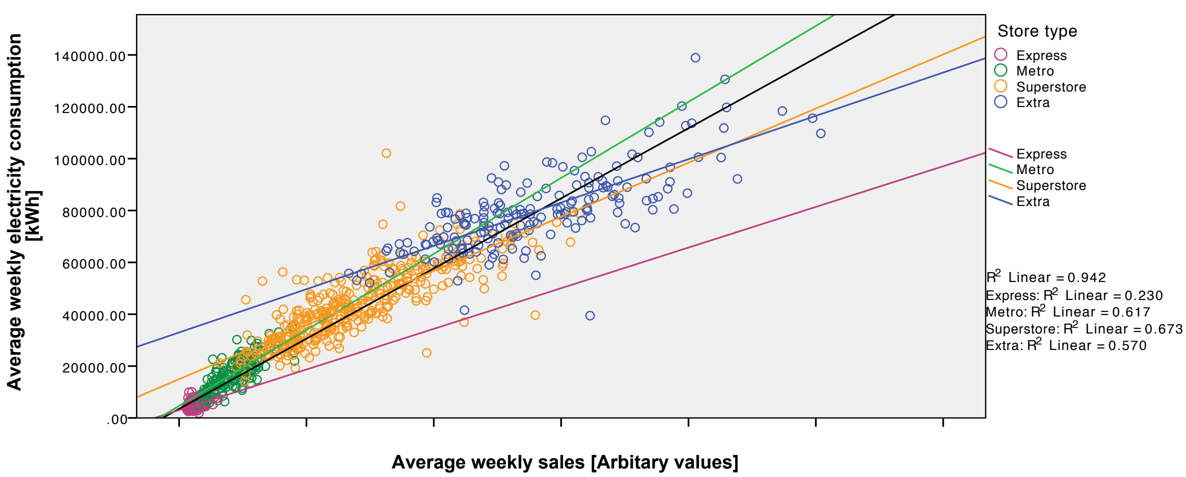

Figure 4.27: Weekly electricity consumption against sales.

Store build date

Another factor that is important to consider is the age of the building. Tesco design standards have been changing over the years, altering both the building materials and the equipment used

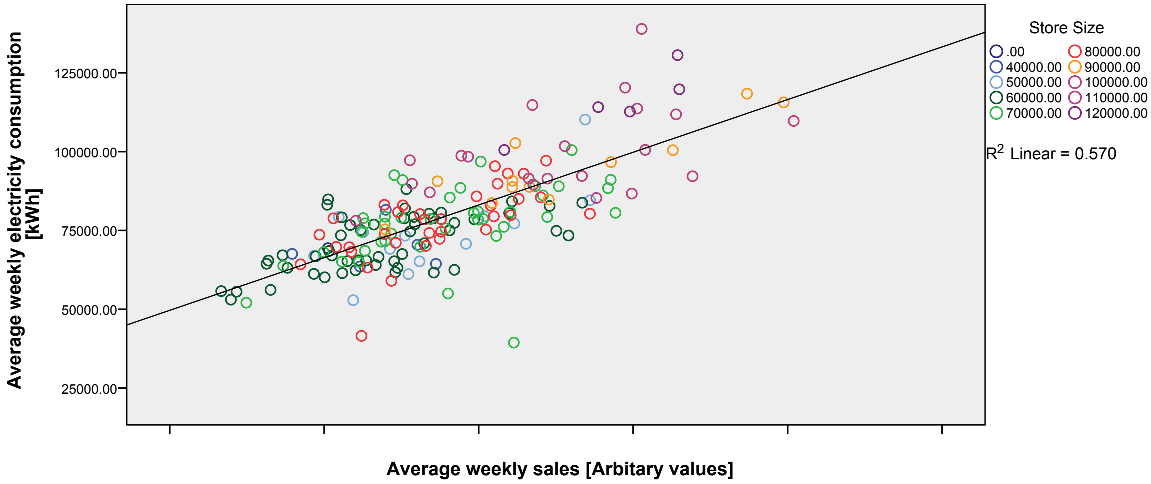

Figure 4.28: Electricity consumption against sales for hypermarkets.

within a store. Building regulations have also changed considerably since the first Tesco store was built in 1929 [58].

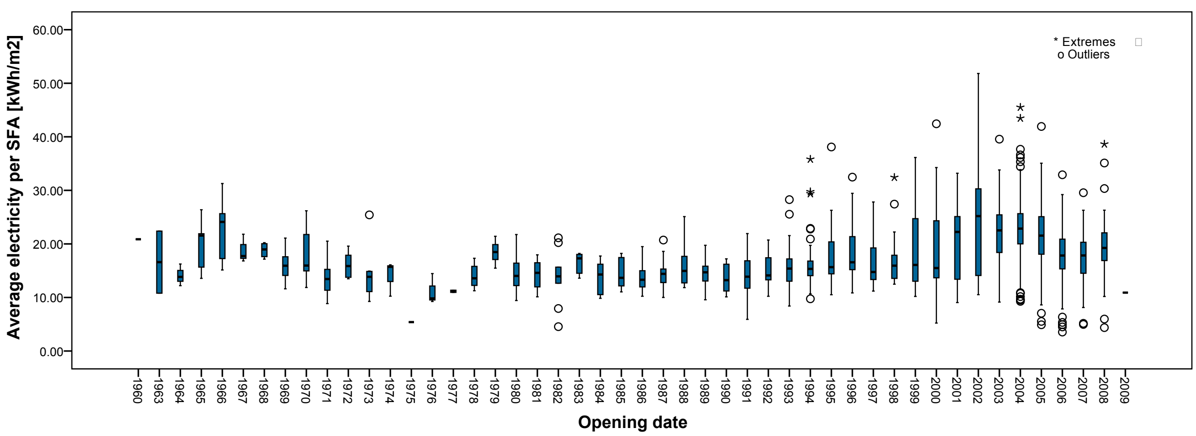

Figure 4.29: The influence of built date on electricity consumption per SFA

The box plot in Figure 4.29 shows how the electricity consumption of stores per square metre varies with built date. There is a small dip in the energy consumption of the buildings built in the 1970s, during the economic/oil crisis, possibly due to the 1974 Conservation of fuel and power provisions for non domestic buildings [59]. This is followed by an overall increase in consumption of buildings built around the 80s. Until 1998 the behaviour is fairly consistent, as the strategy then was to built more hypermarkets (large and efficient) stores. The increase near/after the millennium can similarly be explained by the strategic increase in the number of convenience (smaller and less efficient) stores built by Tesco in order to bring the offer closer to the consumer. As shown earlier in Figure 4.20, convenience stores a have higher electricity consumption per square meter than any other store type.

User behaviour

The energy consumption of buildings does not only depend on the aforementioned factors. User behaviour has an important role as well; surely the efficiency of equipment is limited by the end user. No matter how efficient refrigeration is, if doors are left open (either by customers or staff), packs will consume more than expected. If staff in store overrides lighting schedules, lighting will consume more than expected. If staff switches on ovens before the set time to preheat them, the ovens will consume more than expected. Consequently, this suggests that there is a need for a further investigation into the effects of user behaviour/decisions on the energy consumption of supermarkets (see Christina et. al. [60])

4.4.4 Summary

As part of Study 4, it was found that retail buildings in the Tesco estate have energy consumption values between 230 kWh/m^2 and 2000 kWh/m^2 per year. Whilst there is a high degree of heterogeneity across the store categories, this reduces when inspecting the stores within each category. Store formats differ in terms of size, location, opening times, building type/age and more. Hypermarkets have a smaller variation in electricity and gas intensities compared to the other store categories found in the organisation's stock, as shown in Figure 4.20, which indicates that signals of correlations will be stronger and more readily apparent than with any of the other store categories.

This lead to the decision to pursue the creation of the prediction model based on the hypermarket stores first, and include factors such as: heating and cooling degree days (or outside air temperature), the age of the store, the sales volume of the store, and the operating hours of the store, as well as the operational behaviour of the staff and any other factors that might arise.

4.5 Study 5: Modelling the Energy Consumption of Hypermarkets

This study was undertaken to address Objective 3, *"Develop and implement a methodology for characterising the energy consumption of stores and identifying outliers"* and provide a foundation for answering the thesis' overarching aim of understanding what affects the consumption in supermarkets and creating a model that would help us create more tailored benchmarks for the organisation. It was presented as a journal paper in Energy and Buildings [2], which can be found in Appendix B and should be read alongside this section.

4.5.1 Scope and Aims

As mentioned earlier Study 5 focused on hypermarkets (Extras) as they have a smaller variation in electricity and gas intensities compared to the other store categories found in the organisation's stock, see Figure 4.20, which indicates that correlations will be stronger and more readily apparent than with any of the other store categories. It builds on the work undertaken in Study 4, Section 4.4, where the various factors that affect the electricity and gas demand of stores were identified, and Study 2, Section 4.2, which described the energy budgeting process used by the organisation's energy managers. It aims to create bespoke benchmarks for this store category so that inefficient stores can be identified more robustly. Initially this study was going to include models for each sub-metered electricity demand of the store as well, but after an initial investigation, it was decided that the sub-metered data was not reliable enough to be included/modelled, see Figure 4.21.

4.5.2 Overview of the Study

Study 5 used data from 215 hypermarket stores in the organisation's estate in order to build a model that estimates energy demand, i.e. total annual electricity and total annual gas. Possible factors that influence the energy demand at the aggregated level were identified, both through theoretical concepts and through the previous studies (see Appendix B for a description of all factors). Stepwise multiple linear regression was conducted using the full list of variables in order to make sure that all of the correlations between the variables were taken into account. Through this procedure some variables were found to not have any statistical significance in relation to electricity or gas demand. These were removed from the regression models when identified. A list of 4-5 variables were then introduced into a standard regression analysis. Whilst this procedure has helped us remove variables that have weak signals in the dataset it is possible that influential factors are not accounted for, because they were not found to be statistically significant in the regression models. This could be because the type of variables available in the dataset does not suitably represent these factors. This issue was considered when interpreting the results that follow.

4.5.3 Key Outcomes

Regression analysis was carried out for the three dependent variables separately; electricity demand, gas demand in stores with CHP, and gas demand in stores without CHP.

Total Annual Electricity Demand

Total annual electricity demand was found to be a function of physical size, volume of sales, composition of sales areas and factors related to year of construction. The resultant regression model, Equation 4.7 shows 44.6% of the variability in Electricity Consumption (E) is accounted for by the SFA of a store, and an additional 26.3% is accounted for by the Volume of Sales (VS) of a store. The addition of the Food: Non-Food Ratio (FNF) increased this by 3.7%, while the addition of the Pre-Post 2002 (PP) factor increased it by 1.2%.

$$\begin{aligned} \mathrm{E} = (6.1 \times 10^5) + (3.1 \times 10^2 \times \mathrm{SFA}) + (1.4 \times 10^{-2} \times \mathrm{VS}) + \\ (3.5 \times 10^5 \times \mathrm{FNF}) - (2.1 \times 10^5 \times \mathrm{PP}) \end{aligned} \tag{4.7}$$

This model accounts for 75% R^2_{adj} ($F_{(4,183)}$ = 146.251, p <0.001) of the variance in Electricity and is considered to be moderate to good as few variables prove to be statistically significant and half of the variables have comparatively large regression coefficients. The model also shows that factors related to the composition of product lines, i.e. Food: Non-food Ratio, and the thermo-physical properties of construction, i.e. Pre-post 2002, do have a statistically significant influence on total annual electricity demand.

Although the influence of SFA is as expected, i.e. the larger the store the more electricity it consumes, the strength of its influence is less than expected. In other words, if stores had a linear relationship between SFA and store volume, the relationship between SFA and electricity demand would be stronger. A similar situation was found with usage intensity, as represented by Volume of Sales, where the relationship between usage and electricity demand was found to be statistically significant but not as strong as expected. In this annual electricity demand model, SFA and Volume of Sales could be expected to have a linear type of relationship, where volume of sales increases as the size of store increases, thus resulting in collinearity in the model. However, signals of such collinearity were not evident in the computed collinearity statistics, i.e. the VIF level for each variable, is below an adopted threshold of 5.0 [61]. In other words, the relationship between the size of a store, as represented by SFA, and the number of people frequenting it, as represented by Volume of Sales, is not linear such that it is not accurate to say that larger stores have larger volume of sales.

Composition of product lines, represented by the Food: Non-food Ratio, can affect the relationship between SFA and electricity demand. This is because whilst Food: Non-food Ratio indirectly reflects the relative extent of store floor area dedicated to refrigerated products, such that increasing proportions of floor areas dedicated to food products can be expected to result in increasing refrigeration demand, this ratio is independent of SFA.

Local climatic conditions would be expected to have a direct influence on HVAC cooling loads however, the variables used to represent this, i.e. Heating Degree-Days (HDD), Cooling

Degree-Days (CDD), were found to have no statistical significance. It is be expected that the correlation exists but it is simply too small to emerge explicitly at the aggregated annual level.

Overall the multiple linear regression analysis of total annual electricity demand indicates that at the aggregated annual level, electricity demand can be reasonably well estimated by using the four aforementioned variables; sales floor area, sales volume, food-non-food ratio and pre-post 2002.

Total Annual Gas Demand

Preliminary investigation of total annual gas demand revealed two significant sub-populations of stores without CHP (N=89) and those with a CHP (N=34) (see Figure 4.30). This would be expected to be influential as all the CHP systems are gas driven. The sample was divided into those without and with CHP before stepwise multiple linear regression was conducted. It was also found that annual total gas demand was not normally distributed within both sub-populations and that log transformation did not resolve this. Therefore Gas Intensity (GI) representing Gas Consumption per square meter, see Equation 4.8 below, was adopted as the dependent variable. The use of gas intensity enabled us to determine Gas Consumption more efficiently by taking into consideration the store size.

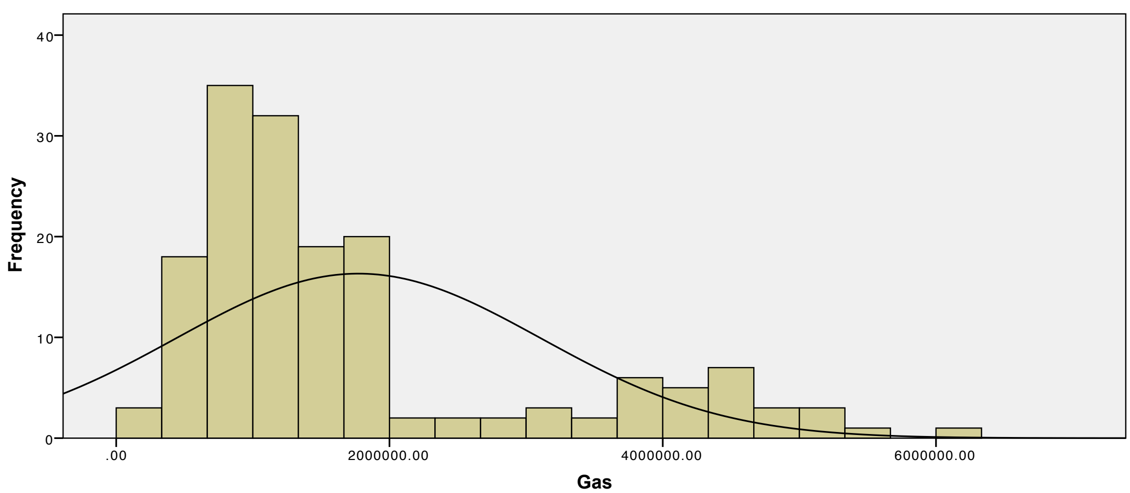

Figure 4.30: Frequency of gas demand [in kWh] in the total sample.

$$\text{GI} = \frac{\text{Gas demand [kWh]}}{\text{SFA}[m^2]} \tag{4.8}$$

Annual gas intensity in stores without a CHP plant In stores without a CHP, gas is used primarily for warm air heating. Heating demand in these systems is a direct function of the volume of air that is heated and, to a lesser degree because of air recirculation, the outdoor climate conditions. Through stepwise regression analysis, annual gas intensity was found to be significantly influenced by factors reflecting store size, volume and the composition of product lines. From the resultant model, Equation 4.9, 29.5% of the variability in Gas Intensity (GI) is accounted for by the SFA of the store and an additional 12.9% is accounted for by the Ceiling Height (CH) of the store. The addition of the number of trading floors (TF) of the store increased this by 3.5%, while the addition of the Food: Non-Food Ratio (FNF)of the store increased it by 0.7%.

$$\begin{aligned} \text{GI} = (3.8 \times 10^2) - (2.0 \times 10^{-2} \times \text{SFA}) + (5.8 \times 10^1 \times \text{FNF}) - \\ (1.7 \times 10^1 \times \text{CH}) - (3.7 \times 10^1 \times \text{TF}) \end{aligned} \tag{4.9}$$

The model is considered moderate and accounts for 50% (R^2_{adj}) of the variance in Gas Intensity ($F_{(4,84)} = 23.65$, p <0.001).

It would be expected that SFA would not be so influential on gas demand intensity as this already accounts for SFA. However, the above results show that increasing store size results in a small but statistically significant reduction in gas intensity, i.e. -0.02 kWh/m^2.yr. This indicates that there is a small but significant increase in energy efficiency of larger hypermarkets.

Similar to electricity demand, climatic conditions, in this case represented by HDD, were not found to be significant. This is particularly interesting as the predominant use of gas is for warm air heating. It is considered that this indicates that the high proportion of recirculation of air in stores makes good use of internal heat gains and that fabric heat loss is minimal.

Whilst the resultant regression model is only moderate it does show that accounting for the range of product types, i.e. food and non-food, is of a similar order of importance as size and volume when predicting annual gas demand intensity. The results show that as the amount of sales floor area dedicated to food products, relative to non-food products, increases, the gas demand intensity increases. This is considered to partly reflect that some food products are presented in cooled cabinets and that some non-food products can have small heat gains, such as electrical products where TV walls, etc. are in use. Further investigation of the influence of more specific product types, e.g. electrical; clothing; ambient food; etc., could result in better prediction of annual gas intensity. Although this model can be considered to be of little practical use in its current form, it indicates that the volume of air to be conditioned, as represented by store volume, and the heat gains of some non-food products, as indicated by Food: Non-Food Ratio, are key factors in gas fuelled energy demands.

Annual gas intensity in stores with a CHP plant In stores with a CHP plant, gas is consumed for heating and to generate electricity. In these stores gas demand is therefore not only driven by the heating demand but also by the amount of electricity that is to be generated. Efficient use of CHP dictates that the use of the system needs to be driven by the demand for heat such that electricity generated is effectively a by-product of generating heat to meet in-store demands. In the context of such efficient CHP management gas demand in stores with CHP could be expected to have similar relationships with factors that affect heat demand as in stores without CHP albeit at a different scale due to comparatively lower efficiency in generating heat in CHP compared to high efficiency boilers.

Stepwise regression revealed that gas consumption in these stores is a function of size, the electrical capacity or rating of the CHP system, as well as the geographical location of the store and the composition of product lines. From the resultant regression model, Equation 4.10 below, 55.3% of the variability in Gas Intensity (GI) is accounted for by the SFA of the building and an additional 16.6% is accounted for by the addition of the Electrical Rating of the CHP plant (ER). The addition of the Easting ($East$) variable increased this by 4.0%, while the addition of the Food: Non-Food Ratio (FNF) increased it by 3.8%.

$$\begin{aligned} \text{GI} = (7.8 \times 10^{2}) - (4.9 \times 10^{-2} \times \text{SFA}) + (1.2 \times 10^{0} \times \text{ER}) - \\ (4.3 \times 10^{-2} \times \text{East}) + (9.0 \times 10^{1} \times \text{FNF}) \end{aligned} \tag{4.10}$$

This model is considered good and accounts for 77% (R^2_{adj}) of the variance in Gas Intensity and is statistically significant ($F_{(4,29)} = 25.32$, p <0.001).

An interesting result is that the Electrical Rating of CHP systems has a significant influence on gas intensity. In these stores increasing size of CHP systems result in small, i.e. R^2_{adj}=1.2 kWh/$m^2.yr$, but statistically important, i.e. Beta weight=0.344, increases in gas intensity. Considering that CHP is most efficiently operated as a function of heat demand this finding suggests a degree of inefficiency in the use of these systems during the measured period. This illustrates that the regression method could be useful in identifying inefficient use or system faults.

The finding that the location of a store, as represented by Easting, is statistically significant is considered to be a reflection of the sample being small, N=34, and having a large number of those stores in the southern part of the UK, see Figure 4.31.

Application of Models

The models described in this section enable quick identification of stores that have had significant changes in energy consumption that warrant further investigation, even though they cannot specify what actions are needed to achieve better energy performance. They can also be used to identify the impact of energy efficiency measures. The electrical model accounts for aggregated operational factors explicitly, i.e. volume of sales representing the number of customers using

Figure 4.31: Location of stores with CHP plants

a store, while the gas models account for operational factors implicitly. From an organisation's management point of view the starting point in ensuring efficient performance of their building stock is identifying how many and which stores have had significant changes in performance for no apparent reason, and then investigating these on a case-by-case basis. The models reported are considered to provide a reliable first order evaluation of the efficient operation of any hypermarket store within the organisation's stock.

4.5.4 Summary

In Study 5 statistical analysis was carried out, which determined the significant factors to be used in multiple linear regression models for electricity and gas demands. Significant factors included the sales floor area of the store, the stock composition, and a factor representing the thermo-physical characteristics of the envelope. Two of the key findings are the statistical significance of operational usage factors, represented by volume of sales, on annual electricity demand and the absence of any statistically significant operational or weather related factors on annual gas demand. The results suggest that by knowing as little as four characteristics of a food retail store one can confidently calculate its annual energy demands. Using the models presented in this study, along with the actual energy consumption of stores, one can isolate stores that are not as energy efficient as expected and investigate them further to understand the reason for poor energy performance. The models reported are considered to provide a reliable first order evaluation of the energy efficient operation of any hypermarket store within the organisation's stock. Deeper understanding of the various demands (i.e. HVAC, refrigeration, lighting) could improve these models further; Study 6 was therefore designed in order to understand the electricity demand for refrigeration in more detail.

4.6 Study 6: Fault Detection in Refrigeration Systems

This study was undertaken to address Objective 4, *"Develop and implement a methodology for identifying conditions in refrigeration systems that lead to increased energy consumption and find early warning signs to be used as part of a proactive maintenance routine"*. As shown earlier, the greatest component of the electricity demand of food retail buildings is the cooling demand of the food refrigeration systems (ranging from 30% to 50%). A better understanding of the electricity demand for refrigeration would enable the development of effective energy management tools, including the evaluation of service and maintenance interventions to reduce operational electricity demand. Study 6 was presented as a conference paper at ASHRAE's Winter conference in 2015 [3], and is included in Appendix C which should be read alongside this section.

4.6.1 Scope and Aims

The initial scope of this study was to include hourly data from sixty stores that were part of a real time metering trial. Unfortunately there was not enough data collected in time for this project, so instead, hourly data from ten stores were collected.

Various methods were developed and employed in the past for the quick identification of faults during the operation of commercial refrigeration systems. The focus of these methods has traditionally been on the temperature of food on the shop floor. The aim of Study 6 is to enhance the existing fault detection methodologies employed by the organization, by enabling the identification of events that cause an increase in electricity demand of the refrigeration systems. More specifically it aims to gain insights to the operational behaviour of the systems in order to identify conditions in refrigeration systems that lead to increased electricity demand and then find the early warning signs to be used as part of a proactive maintenance routine. For this reason, the Failure Mode Effects Analysis (FMEA) method was initially considered as a way of finding which faults occur more often. It was soon discovered though that each technician has their own way of interpreting and describing faults and it was impossible to understand what each of them meant. Therefore the study was focussed on the operational data that was available, Table 4.2.

4.6.2 Overview of the Study

Study 6 presents a method that analyses data from refrigeration systems and enables a more straightforward identification of faults. Data mining methods were employed to remove known operational patterns (e.g. defrost cycles) and seasonal variations, as explained in Section 3.2.7. The resulting dataset was then analysed further to understand the events that increase the electricity demand of the systems in order to create an automatic identification method.

4.6.3 Key Outcomes

The key outcomes of this study can be summarised by looking at two examples of faults identified.

Example A: Low Temperature Pack - Missed Opportunity

Figures 4.32 to 4.37 present the electricity consumption data of the pack and how it was transformed using the methodology presented in section 3.2.7. Figure 4.32 shows the original elec-

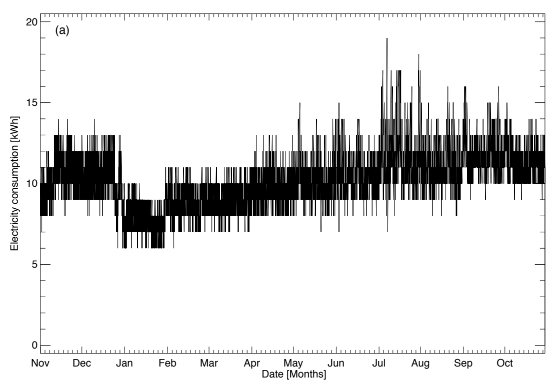

Figure 4.32: Electricity consumption of example A

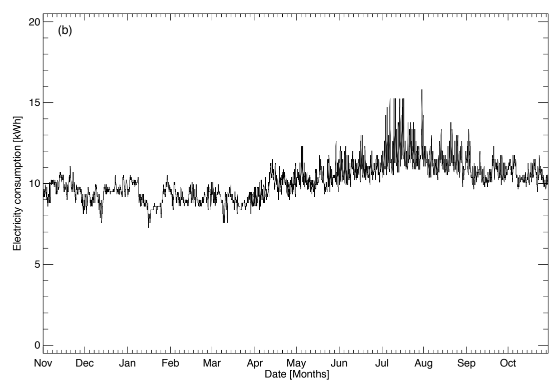

Figure 4.33: The modelled (Y) electricity consumption of example A

tricity consumption data of example A. The electricity consumption in Figure 4.32 seems to be very stepwise, this is because the consumption is measured to the nearest kWh, i.e. no decimals are recorded. By looking at this figure, one cannot be certain if there was a fault in the operation of this pack as there is only a small step change in the consumption towards the end of December. Figure 4.33 shows the regression model, equation 3.2.7, for the same store. Figure 4.34 shows the FFT transform of the data, indicating the peaks that were removed, and the 12-hourly peak that cannot be explained with the available information. The final dataset, and the outlier data selected for investigation, are indicated in Figure 4.35.

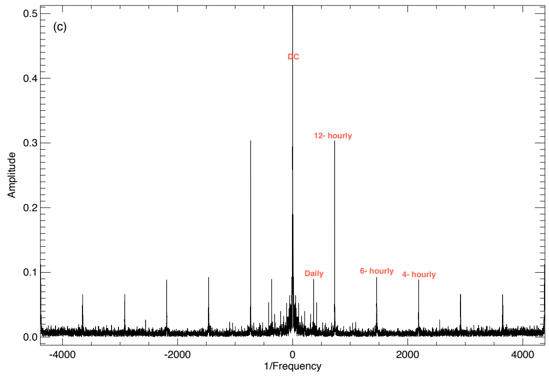

Figure 4.34: FFT of the electricity consumption of Example A

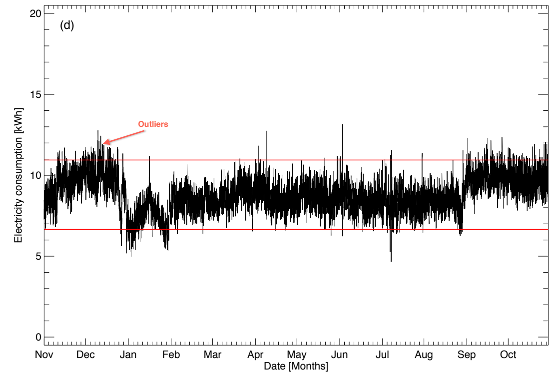

Figure 4.35: The resulting dataset of Example A, indicating outliers

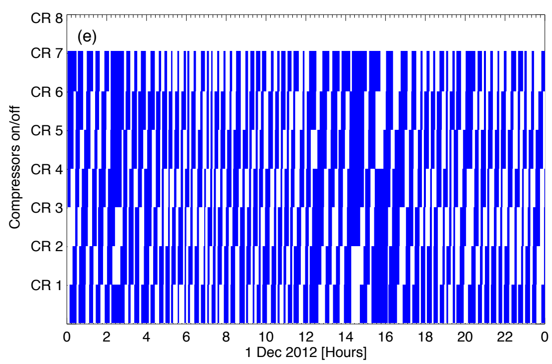

Figure 4.36: The compressor run times of Example A on Dec 1, 2012

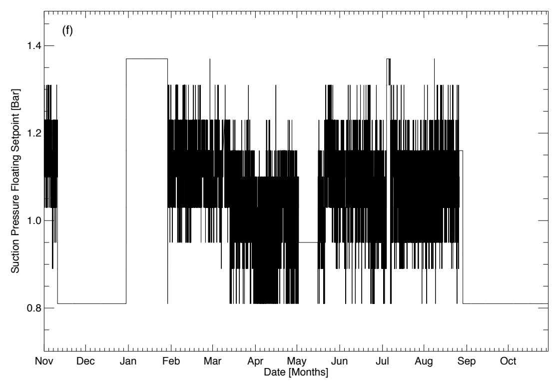

Figure 4.37: The suction pressure floating set point of Example A over the whole year

The data for the outlier periods of time was closely investigated and it was found that the compressor run times, CR, of the pack were much higher during those periods of time (Figure 4.36). This was expected, as the more time the compressors are run, the more electricity they consume. However, there were no obvious reasons for the extra compressor need. By looking at the suction pressure floating set point ($P_{S-setpoint}$), Figure 4.37, this becomes clearer. $P_{S-setpoint}$ was not floating as expected; it was set to the minimum value (0.81 bar) for both of the high electricity consumption periods. This has caused the need for more compressors to be running at any given time to achieve the required suction pressure, leading to higher electricity consumption. Allowing the set-point to float in this example would have saved 20% of the pack's electricity consumption for that period of time (calculated from Figure 4.35).

Example B: Low Temperature Pack - Oversized System

Data for this store is presented in Figures 4.38 to 4.41. After applying the methodology to the original electricity data (Figure 4.38), it became clear that there was a 15% reduction in the electricity consumption occurring on February 5, 2013, Figure 4.39. This was caused by the installation of passive display doors that do not have anti-fog heaters installed. Anti-fog heaters use electricity to generate heat which helps in preventing moisture from forming on the display door, the passive doors do not require any power. As seen in Figure 4.4, the direct electricity consumption saving from this is not included in the data used in this work, as it is affecting the case consumption instead of the pack consumption. However, there was an indirect effect of this installation, as the new passive display doors do not produce any heat, which reduced the overall cooling demand of the system.

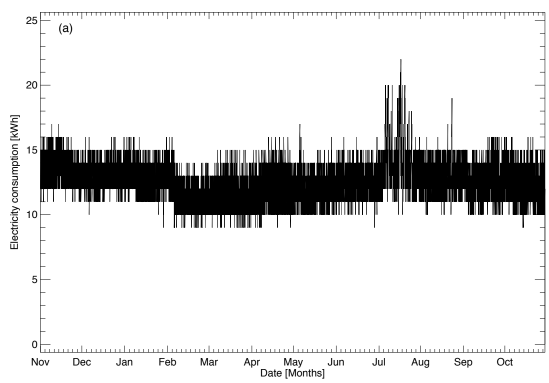

Figure 4.38: Electricity consumption of example B

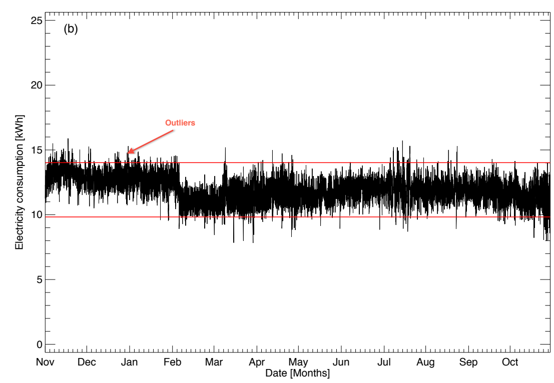

Figure 4.39: The resulting dataset, indicating outliers for example B

The rest of the store's data was fully investigated, and it was identified that after the installation of the new doors the suction pressure of the pack was floating around the minimum value of 0.81 bar, Figure 4.41. This could be considered normal, if the cases were at a higher temperature than the set-point, but there were no temperature alarms from the cases. Additionally the compressors in the pack were found to drop off too quickly, after 5 minutes of operation (Figure 4.40). Both of these issues were unusual, and after discussions with the refrigeration engineers, it was concluded that both concerns could be caused by the following factors: (i) the installation of the passive doors caused the pack to be oversized for the number of cases connected to it, or (ii) a shortage of refrigerant in the system. As there were no records of temperature alarms from the cases, it can be assumed that there was enough refrigerant in the system; therefore this is most likely to be an over-sizing problem. Fitting more cases to this pack, or switching one of the compressors to a variable speed would allow this pack to work more efficiently and use less energy.

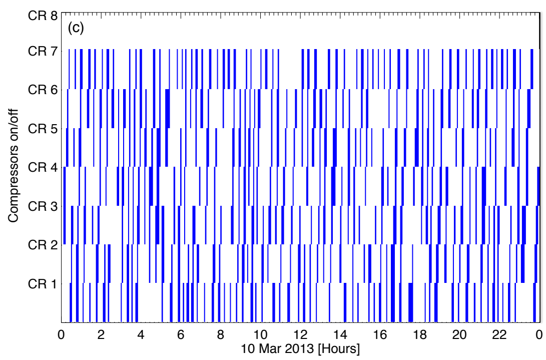

Figure 4.40: The compressor run times of Example B on March 10, 2013

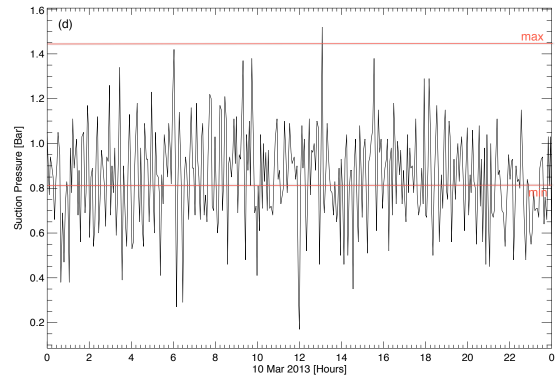

Figure 4.41: The suction pressure of Example B on March 10, 2013

4.6.4 Summary

The method used for Study 6 analyses the electricity consumption data from refrigeration systems and enables a more straightforward identification of faults. The examples included have demonstrated that this method can form part of a more advanced automatic fault detection solution; potential faults were difficult to identify in the original electricity dataset. However, treating the data with the method described in this work has made it simpler to identify potential faults, and look for probable causes. It was also shown that by monitoring the suction pressure of the packs, alongside the compressor run-times, one could identify further opportunities for electricity consumption reduction. Study 7 was hence designed to use the method developed for Study 6 and analyse data from more refrigeration packs in order to validate this method.

4.7 Study 7: Validation of the Fault Detection Method

Study 6 has facilitated the development of a method which enables a more straightforward identification of faults. Study 7 has hence built on those learnings and used the method developed to analyse data from different refrigeration packs in the organisation's estate.

4.7.1 Scope and Aims

The aim of this study was to evaluate the method proposed in Study 6, and validate that it enables a more straightforward identification of faults. A secondary aim of the study was to test the findings from example A; validate the savings from enabling the floating of the suction pressure set point. The scope was therefore limited to data from low temperature refrigeration packs, which were fitted with a specific type of controller and did not have the floating suction pressure enabled.

4.7.2 Overview of the Study

As mentioned earlier, Study 7 has followed the method proposed in Study 6 for a different sample of stores. From this new sample of stores, the most interesting examples have been selected and are presented below.

4.7.3 Key Outcomes

The key outcomes of this study can be summarised by looking at two examples from different stores.

Example C: Low temperature pack - Missing data

Data for Example C is presented in Figures 4.42 to 4.44. After applying the first parts of the method to the original electricity data (Figure 4.42), it was apparent that the initial part of data (40 days) needed to be removed before the regression model was built. The resulting model

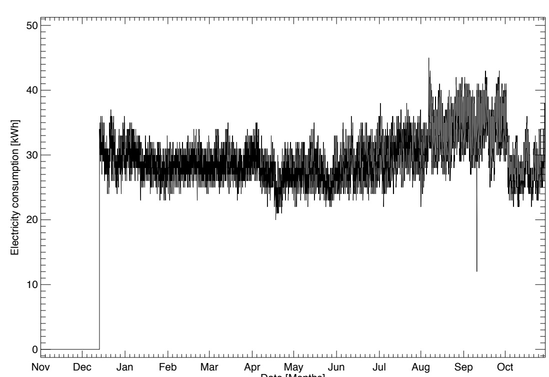

Figure 4.42: Electricity consumption of Example C

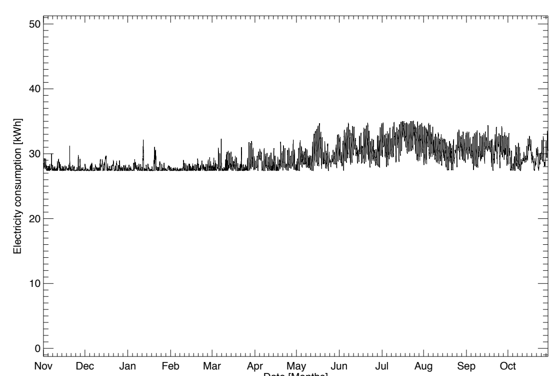

Figure 4.43: The prediction model for the consumption of Example C after excluding the non-regular data

after the removal is presented in Figure 4.43, while the final result is presented in Figure 4.44, and it shows that two periods need to be investigated, January and August to September.

As in previous examples, the operational data of the system were investigated, and it was found that the excess electricity consumption in January was caused by a high discharge pressure (averaging at 15 bar). No specific problem was found to be causing the excess electricity

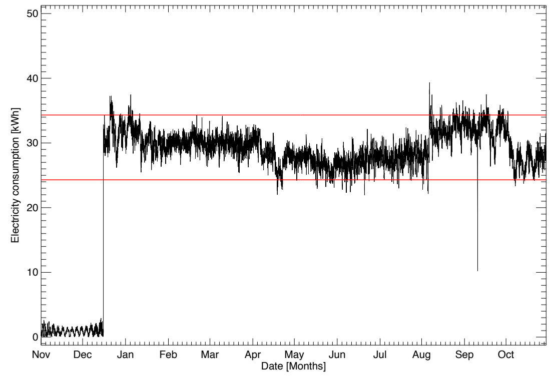

Figure 4.44: The updated resulting graph of Example C

consumption in August to September, this could be caused by parameters not measured, or faults in the HVAC system not reported by the in-store technician.

Example D: Three Steps of Suction Pressure Set Points

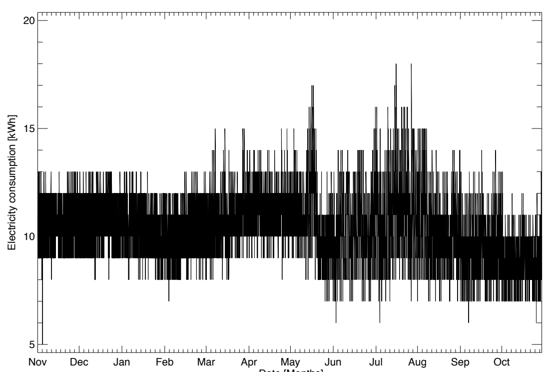

Figure 4.45: Electricity consumption of Example D

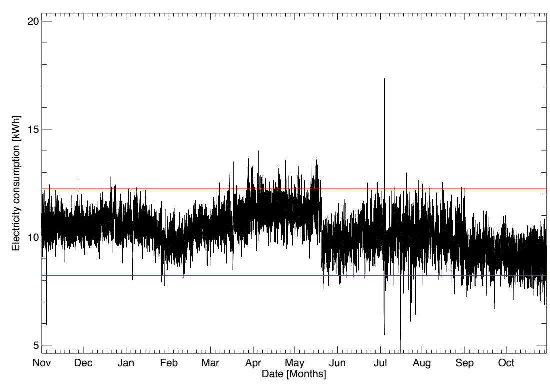

Figure 4.46: The resulting dataset for Example D

The data from Example D (Figure 4.46) shows an increased electricity consumption between November 2013 and mid-May 2014. After further investigation it was found that one reason for the excess electricity consumption was the low set point for suction pressure (Figure 4.47). A second step downwards was observed later in the year, in September 2014, which was caused by a further increase of the suction pressure set point. The operational and maintenance data were analysed further, but no explanation was found for the dip in electricity consumption in February 2014.

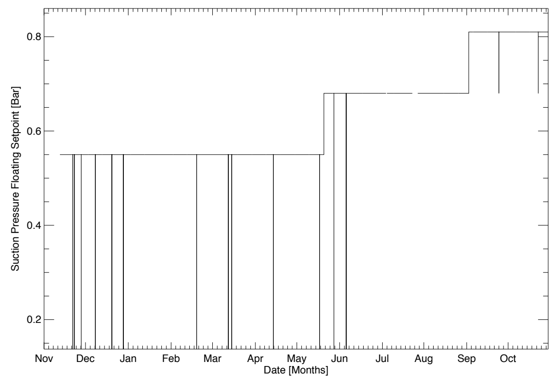

Figure 4.47: The suction pressure of Example D

4.7.4 Summary

Study 7 has shown that the method proposed for Study 6 can be used as an enabler for a more straightforward identification of faults. The method requires complete datasets in order to perform accurately. Any gaps in the data influence the regression model.

Increasing the suction pressure set point, or allowing it to float, can bring savings in electricity consumption. This is because it allows the system to operate with a lower pressure difference when the temperature on the sales floor is maintained. The savings can be higher in the winter months because it is easier for the system to reach and maintain the correct case temperature and then allow itself to float higher until the temperature in the cases is raised. Enabling the floating of the suction pressure in a pack will not automatically bring savings in electricity consumption. This functionality has been developed as an energy saving measure but it will only work when the whole system is stable. For example it will not work if there is insufficient refrigerant in the system as the system would need a lower suction pressure in order to achieve the correct temperature in the cases.

Another finding of this study was that any faults that cause a higher sensitivity to outside air temperature will not be identified with this method as the basis of the model is the assumed dependency on it. This issue can be overcome by clustering various packs together and creating a cluster-wise regression model.

4.8 Summary

This chapter has presented the work undertaken during this project. Each of the studies was discussed separately, including the scope and aims, an overview, and the key outcomes. The seven studies undertaken were approached as different episodes of the same story. Learnings from the initial studies were used in the subsequent studies in order to address the overarching aim of the research project, and the four objectives set at the beginning of the project.

Chapter 5: Findings and Implications

This final chapter summarises the key findings of the research, the contribution of this project to existing theory and practice, and the implications and impact on the sponsor organisation and wider industry. The chapter concludes with recommendations for future research and a critical evaluation of the research.

5.1 The Key Findings of the Research

The overarching aim of this EngD was to understand the energy consumption of the Tesco estate, identify best practice, and find ways to identify opportunities for energy reduction. The specific objectives are detailed in Section 1.2, key findings relating to each of these objectives are summarised below:

Objective 1:

A literature review was conducted covering the topic of energy consumption in the retail sector, reviewing benchmarks for this type of buildings from UK, Europe and the US. Related data analysis techniques used in the industry or presented in the literature were also reviewed. This revealed that there are many different analysis and forecasting techniques available, and that they fall into two different categories:

1. Techniques that require past energy consumption data in order to calculate the future consumption, such as statistical regression, a fairly easy to understand method, and artificial neural networks, a method that has the ability to 'learn' new parameters and can adapt.

2. Techniques that are able to estimate the energy consumption of buildings, based on the specific building's characteristics, such as thermal simulation models. These are usually used for new buildings, but they could also be used in benchmarking exercises, in order to achieve best practice guides.

Gaps in the industry knowledge were identified, and it was suggested that better analytical tools would enable the industry to create more accurate energy budgets for the year ahead leading to better operating margins. Objective 2 was therefore aimed at understanding the current state of consumption in the organisation's estate.

Objective 2:

Benchmarks for the organisation's buildings were calculated. Retail buildings in the Tesco estate were found to have electrical intensity values between 230 kWh/m^2 and 2000 kWh/m^2 per year. Still the average electrical intensity of these buildings in 2010-11 was found to be less than the calculated UK average of the 2006-07 period. The effect of weather on gas and electricity consumption was investigated, and was found to be significant ($p<0.001$). There was an effect related to the day-of-the-week, but this was found to be more related to the sales volume on those days. Sales volume was a proxy that was used to represent the number of customers walking through the stores. The built date of the building was also considered to be an interesting factor, as the building regulations changed significantly throughout the years and the sponsor did not usually carry out any fabric work when refurbishing the stores. User behaviour was also identified as an important factor that needed to be investigated further, relating to both how the staff perceives and manages the energy consumption in their work environment, as well as how the customers use the refrigeration equipment.

Objective 3:

Following a statistical analysis, significant factors were determined and used to create multiple linear regression models for electricity and gas demands in hypermarkets. Significant factors included the sales floor area of the store, the stock composition, and a factor representing the thermo-physical characteristics of the envelope. Two of the key findings are the statistical significance of operational usage factors, represented by volume of sales, on annual electricity demand and the absence of any statistically significant operational or weather related factors on annual gas demand. The results suggest that by knowing as little as four characteristics of a food retail store (size of sales area, sales volume, product mix, year of construction) one can confidently calculate its annual electricity demands. Similarly by knowing the size of the sales area, product mix, ceiling height and number of floors, one can calculate the annual gas demands. Using the models created, along with the actual energy consumption of stores, stores that are not as energy efficient as expected can be isolated and investigated further in order to understand the reason for poor energy performance.

Objective 4:

As part of this objective, data from 10 stores were investigated. This included data from the refrigeration systems, such as electricity consumption of the pack, outside air temperature, discharge and suction pressure, as well as percentage of refrigerant gas in the receiver. Data mining methods (regression and Fourier transforms) were employed to remove known operational patterns (e.g. defrost cycles) and seasonal variations. Events that have had an effect on the electricity consumption of the system were highlighted and faults that had been identified by the existing methodology were filtered out. The resulting dataset was then analysed further to understand the events that increase the electricity demand of the systems in order to create an automatic identification method. The cases analysed demonstrated that the method presented could form part of a more advanced automatic fault detection solution; potential faults were difficult to identify in the original electricity dataset. However, treating the data with the method designed as part of this objective has made it simpler to identify potential faults, and isolate probable causes. It was also shown that by monitoring the suction pressure of the packs, alongside the compressor run-times, one could identify further opportunities for electricity consumption reduction.

5.2 Contribution to Existing Theory and Practice

The findings of this research project can be summarised as four contributions to the existing theory and practice.

Contribution 1

The first contribution consists of monitored data for energy consumption and power demand profiles of supermarkets. [Appendices A, B, and C]

Even though the electricity and gas consumption of retail buildings has been monitored for decades, this level of granular data has not been available to researchers directly. This project has produced research papers based on this data, and has provided an insight into the various data collected by a multinational organisation.

Contribution 2

The second contribution consists of a cross-disciplinary investigation into the factors influencing electricity and gas demand of supermarkets. [Appendices A and B]

One of the most interesting findings was that sales volume affects the electricity consumption of a store significantly. It was found that stores of different sizes consume the same amount of electricity when they produce a similar volume of sales.

Contribution 3

The third contribution consists of three validated models for estimating electricity and gas demand profiles of supermarkets. [Appendix B]

These models have been shown to be able to differentiate between energy efficient and inefficient stores by taking into account a small number of variables.

Contribution 4

The fourth contribution consists of a validated method for modelling the electricity demand profiles of commercial refrigeration systems based on weather. [Appendix C

This method has been shown to help identify conditions where refrigeration systems are not as energy efficient as in the past and so allow for interventions to be made.

5.3 Implications/Impact on the Sponsor

This project has used data from various databases collected by the sponsoring organisation and provided a more detailed understanding of the main drivers of energy consumption in Tesco stores. It has also enabled the identification of stores that are energy inefficient and performing outside of best practice, by providing the regression equations presented in Section 4.5.

The findings from this project have influenced the energy analytics team to start using regression models as part of their forecasting tools. The maintenance team is also using the insights from Studies 6 and 7 to improve the performance management of their contractors. In general, this project has provided the tools and the confidence to the energy managers of the sponsor to use the energy data, gather insights and make data driven decisions.

The method presented in Section 3.2.7 can aid in delivering better control and energy reduction targeting in refrigeration systems. It can also have a high impact in assisting the energy managers to find inefficiencies in the refrigeration systems. One of the findings of Studies 6 and 7 was that floating the suction pressure can bring electricity savings of up to 20% in refrigeration systems where the suction pressure set points were set very low. Rough estimations bring the savings to £1m if this is enabled in all of the refrigeration systems that do not currently have this functionality enabled.

One of the incidental findings of the project was that the engineering, energy and maintenance teams needed to work closer together in order to achieve more energy efficient buildings. It was a recurring theme, from the beginning to the end of this project that the three teams were not communicating adequately; issues that could have been resolved at the design stage were not identified until post implementation. Similarly, while the engineering team was designing for energy efficiency and changed various settings in the refrigeration systems, the maintenance team was not informed, and hence altered the settings as soon as they were made aware of them. The three teams are now working closer together under the same director, which has improved the communication and between the three teams.

5.4 Implications/Impact on Wider Industry

This project has provided an insight into the data monitored and collected by a large multichannel organisation such as Tesco. It has shown how this data can be analysed to provide further insights and learnings.

Statistical methods have been presented which are relevant to any energy manager, whilst the regression models presented in Study 5 can inform new and more precise energy benchmarks for the retail industry. The same models will probably not represent stores built/owned by different retailers, but the method used to create these models can be applied to different datasets. Similarly, the analysis of the monitored data from the refrigeration systems has demonstrated how inefficiencies can be determined, and inform maintenance routines. The same method can be used with different data sets by any other retailer. Further investigation involving several retailers is recommended to develop this into a more robust method.

5.5 Recommendations for Industry/Further Research

Collaborations between industry and academia are not straightforward to implement, usually due to the different time-scales the two sectors are working towards. This project has shown that both academia and industry can benefit from collaborations such as this. Large organisations such as Tesco usually do not have the time, or the resources, to explore various research methods and carry out long research projects. Similarly, academia often lacks real-world data to perform such analysis. The author would like to encourage further collaborations between the two, and make the following recommendations:

1. When installing submetering, ensure correct installation/coverage of meters.

2. Ensure that the IPMVP [57] is used when evaluating energy efficiency projects.

3. More specific benchmarks are needed for supermarkets, these could include variables such as product mix and expected sales volume/footfall.

4. Make use of the available data. Many organisations collect data about their buildings, either because of regulations or for billing purposes but do not query this data to understand their consumption. It is suggested that new research projects should take advantage of these data from multiple organisations in order to generate more general insights and improve the knowledge of the industry.

5. New research projects should use more data mining techniques, such as clustering, in order to understand why some buildings/ equipment behave differently from the rest of the sample.

6. Further research is also needed to understand the operational performance of refrigeration systems. End users, such as the project sponsor, need to work closer with designers and manufactures of refrigeration systems in order to understand the performance of their systems during normal operation and standard maintenance routines.

7. Further research in the area of fault finding is also needed, concentrating on the in-situ performance of systems rather than lab performance in order to understand the effect of different faults on each system.

5.6 Critical Evaluation of the Research

This research project was originally set out to achieve a very broad research aim and the initial research objectives included the construction of DTS models for each type of store. Those initial objectives were re-evaluated 18 months into the project and agreed by all involved that DTS models were not accurate enough to provide reliable output as part of this project. Retail buildings vary too much in terms of building materials used, location, orientation, and even occupant behaviour (customer patterns) that the DTS models were found to be inadequate to represent them and were therefore removed from the scope of this project.

The focus of the research was then directed towards using the metered data of the sponsor and providing insights through analysis. One of the first limitations of this work is that it did not use the submetered data as extensively as possible. The reason for this was that the submetering strategy of the organisation had changed throughout the years, and lighting metered in one store was not the same as lighting metered in a different store; i.e. in some stores lighting only covered sales floor lighting, while in others it covered carpark lighting, office lighting, and small power as well.

Another limitation of the research is that it only used one specific type of store when creating the regression models in Section 4.5. Study 5 could be repeated with the inclusion of all store types, as well as more granular data, such as weekly, or even hourly consumption. At the time that the research was undertaken, a statistician had advised against the use of time dependent data in regression models, but it has since become clear that other professionals make use of time dependent data, but exclude the time component in their analysis. For example the IPMVP [57].

Despite these limitations, this research project has successfully achieved its overarching aim of finding ways to identify opportunities for energy reduction. Four specific objectives were fulfilled, generating key outcomes that contributed to the achievement of the thesis' aim. The research has provided three models for estimating energy consumption of large supermarkets. Furthermore a method for creating model for refrigeration systems was proposed and validated; this method allows for a quick identification of 'faults' that cause an increase in the electricity consumption of those systems. Cumulatively, the outcomes of this project have a great potential to improve current practices for energy management in non domestic buildings.

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Appendix A: Paper 1

Reference:

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Energy Consumption Prediction Models for the Retail Sector

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Abstract

The ability to analyse and accurately forecast future events is becoming increasingly important as most management decisions depend on them. This is especially evident for the retail sector, mainly because of the small margins that the sector is working within, alongside the increasing prices of electricity and gas. Tesco, as the market leader, wishes to be at the forefront of research and make a step change in their ability to forecast and reduce the energy consumption of their buildings.

This work presents the various benchmarking methods available in the UK, Europe and the US, including CIBSE TM46, ISA, and ASHRAE benchmarks. The mathematical techniques employed to access the predictions obtained using these benchmarking and forecasting methods are discussed as well as the analysis and forecasting methods used by the industry.

The research reported throughout this paper uses energy data obtained from the Tesco estate to draw correlations with weather, sales' floor area, sales and other factors that might affect the energy consumption. Initial results regarding the effect these factors have on the energy consumption of buildings in the Tesco estate are presented.

Keywords

Energy Consumption, *Tesco*, *Prediction Model*, *Retail*, *Benchmarks*

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A.1 Introduction

Currently in the UK there are approximately 8000 supermarkets and superstores occupying more than 300m^2 of sales area. Most of these stores (5400) are operated by the four largest supermarket chains: Tesco, ASDA, Sainsbury's and Morrisons [1] At the beginning of 2011 Tesco was reported to be the market leader, with a share of 30.3%, followed by ASDA at 16.9%, Sainsbury's at 16.5% and Morrisons at 12.3%. The remaining 24% was shared by smaller chains such as Somerfield, Waitrose, Iceland, Co-op and other multiple chains and independents [2]

Supermarkets are responsible for more than 3% of the total electricity consumption in the UK and around 1% of the total CO_2 emissions of the UK [3] As stated in [4]

"Supermarkets are seeking to improve energy efficiency in order to make cost savings and enhance their image".

As the market leader, Tesco aims to be at the forefront of research and make a step change in improving the energy efficiency of their buildings. The company is operating more than 2000 stores in the UK. Specifically, on the 1st of November 2010, its estate was composed of 212 *Extra* stores[1], 470 *Superstores*[2], 186 *Metros*[3] and 1285 *Express* stores[4].

In its latest Corporate Responsibility Report, Tesco pledged to become a "*zero-carbon business by 2050".* There is no official scientific explanation for *zero-carbon*, so, it is suggested that Tesco is aiming to become a *carbon neutral* business. Oxford English Dictionary defines "carbon neutral" as:

Making or resulting in no net release of carbon dioxide into the atmosphere, especially as a result of carbon offsetting.

For a company of this size, it is a significant challenge to become *carbon neutral* as there are many factors affecting their footprint, such as electricity consumption in stores and offices, refrigerants, transportation of products, and even business travel [5]

In 2010 the total electricity consumption of all the UK Tesco stores amounted to 1% of the UK's energy consumption [6].Therefore, it is significant to note that by reducing Tesco's consumption by 10%, the whole consumption of the UK can be reduced by 0.1% (0.35GWh).

Section 2 of this paper presents the various methods reported in the literature for analysing, assessing and forecasting the energy consumption of commercial buildings. It documents benchmarking methods and statistics published internationally and introduces forecasting techniques used within the industry. Methods used for data gathering and quality are included in Section 3; Section 4 includes initial results regarding the factors that affect the energy consumption of stores. Conclusions are drawn in Section 5 along with suggestions for further research.

A.2 Energy Benchmarks and prediction techniques

A.2.1 UK Benchmarks

As the British Retail Consortium website [7] advises, British retailers are impacted by two government regulations: theDisplay Energy Certificates (DECs) and the Carbon Reduction Commitment (CRC) energy efficiency scheme. The DECs are based on metered energy consumption and should reveal how effectively a building is being operated. They aim to motivate the

[1] *Extra* stores have a net floor area over 60 000ft^2 $\approx$ 5 570m^2.

[2] *Superstores* have a net floor area between 20 000 - 50 000ft^2 $\approx$ 1 860 - 4 650 m^2.

[3] *Metros* have a net floor area between 7 000-15 000ft^2 $\approx$ 650 - 1 400 m^2.

[4] *Express* stores have a net floor area under 3 000ft^2 $\approx$ 280 m^2.

building operators to become more energy efficient by raising public awareness of energy use. In terms of calculating the Operational Rating for each building, the following are taken into account:

"*-Category of the building (as described by TM46, CIBSE)*
-Location (postcode, building name, address)
-Energy consumption (meter readings or suppliers estimates) and measurement period
-Building (or site) area and how it has been defined
-Separable energy uses- if any
-Recorded hours of occupancy"

Building Regulations Approved Document L2A (2006) [8] defines the total useful floor area (TUFA) as the: *"Total area of all enclosed spaces measured to the internal face of the external walls, that is to say it is the gross floor area as measured in accordance with the guidance issued to surveyors by the RICS."*

TM47 provides the conversion factors of Table A.1 for the buildings of which the area was not measured as TUFA [9].This introduces inaccuracies into the calculation, as not all large food stores have a TUFA twice as big as their sales' floor area (SFA).

The CRC energy efficiency scheme allows the calculation of CO_2 emissions using the total electricity, gas and any other fuel consumption of a building/company [10].

CIBSE TM46 [11] presents energy benchmarks for 29 categories of buildings and it expresses the benchmark values in term of energy use per floor area (kWh/m^2). TM46 provides two values for each building: the electricity typical benchmark and the fossil-thermal typical benchmark. The benchmark data from TM46 are summarized in Table A.2.

A.2.2 US Benchmarks

ASHRAE, the American Society of Heating, Refrigerating and Air-Conditioning Engineers publishes benchmarks [12] and the Standard Benchmark Energy Utilization Index [13] in US customary units. Energy consumption values are quoted in kBtu/ft^2 while the guide provides a different value for each type of building in each of the sixteen different climate zone cities. ASHRAE also divides the buildings according to the year they were built: new-build, post-1980 and pre-1980; these values are summarized in Table A.2. The floor area used for these calculations is defined as the:

"Total interior floor area of a building's spaces, measured from the inside surface of the exterior walls or from the interior surface of walls in common with adjoining buildings. The area of interior columns and pillars is included in this measurement. This metric is measured on a floor-by-floor basis and consists of all enclosed spaces, including the area of interior walls, basements, mezzanines, penthouses, equipment rooms, vertical penetrations on each floor (such as elevator shafts, and stairwells), and interior parking. It does not include open covered walkways, courtyards with no roof, balconies, and canopies" [14, 15]

Another benchmarking and rating system, mainly used in the US, is the Leadership in Energy and Environmental Design (LEED) [16]. In order to obtain LEED certification a building needs to comply with one of the following:

Category	*Name*	*Brief description*	*Approved alternate floor area*	*Default multiplier applied to obtain TUFA*
C1	General office	General office and commercial working areas	Net lettable area (NLA) as defined in RICS *Code for Measuring Practice*	1.25
C3	General retail	General retail and services	Gross floor area measured in SFA	1.80
C4	Large non-food shop	Retail warehouse or other large non-food store	Gross floor area measured in SFA	1.80
C5	Small food store	Small food store	Gross floor area measured in SFA	1.35
C6	Large food store	Supermarket or other large food store	Gross floor area measured in SFA	2.00

Table A.1: Conversion factors for other measures of floor area to TUFA, table from [9]

- ASHRAE standard ISO 90.1-2010, use modelling software to simulate energy consumption/savings of the building.
- ASHRAE Advanced Energy Design Guide, which is a descriptive guide describing ways to save energy, such as refits.
- Advanced Buildings Core Performance Guide in addition to a credit earning system, to grade buildings [17].

A.2.3 EU Benchmarks

The International Sustainability Alliance (ISA) published a report in 2010 [18] giving different benchmark values for the energy consumption of buildings in Europe. ISA does not provide the reader with more specifics on how the energy intensity of the buildings is calculated. The benchmark values published by ISA are also summarised in Table A.2.

The European Commission for energy defines the area of buildings in square meters of useful floor area (UFA) [19]

"The UFA of a building is measured within its external walls, excluding:
-Construction areas (e.g areas of demarcation components, supports, columns, pillars, shafts, chimneys),
-functional areas for ancillary use (e.g. areas occupied by heating and air conditioning installations or by power generators),
-thoroughfares (e.g. areas of stairwells, lifts, escalators)."

BREEAM (Building Research Establishment Environmental Assessment Method) is an "*environmental assessment method*" and "*rating system*" [20] It is primarily used in the UK but has also been developed for other European countries, such as the Netherlands and Spain. There are various schemes one can follow, including BREEAM New Construction, BREEAM Refurbishment, and BREEAM In-Use; depending on the construction stage of the building. The Building Research Establishment (BRE) has not developed independent energy consumption benchmarks for the rating system, but uses the ISA benchmark values. The scheme covers ten categories including *Management, Energy, Transport,* and *Innovation*. In each category the impact of the building on the environment is assessed, using a performance target and assessment criteria. If the target is achieved, then a number of BREEAM credits are awarded, depending on how many credits are available for that category. For example, for the *Energy* category, the assessor will look for sub metering and energy efficient building systems amongst others [21].

Type of Building	*CIBSE (2008) (kWh/m^2)*	*ASHRAE (New-Built) (kWh/m^2)[22]*	*ASHRAE (Post-1980) (kWh/m^2)*	*ASHRAE (Pre-1980) (kWh/m^2)*	*ISA (2010) (kWh/m^2)*
Supermarket	505	565	700	710	819
Office	215	136	205	226	377

Table A.2: Typical benchmark values as published by various organizations.

The literature includes several other benchmarking methodologies. In a paper by Chung [23] these are reviewed and divided into the following categories:

- Simple normalization (Simple)- usually based on energy consumption data and floor area.
- Ordinary Least Square (OLS)- also called simple regression analysis as it involves the analysis of data using a simple regression model. [24]
- Data Envelopment Analysis- a multi-factor productivity analysis model.
- Stochastic Frontier Analysis- a technique that separates the error components of the OLS method in order to calculate the efficiency of the building and the users' separately.
- Model-based method- a simulation software is used evaluating the energy consumption of various systems. This method is usually incorporated within the building's design procedure and not used in direct benchmark calculations.

- Artificial Neural Networks (ANNs)- these can be used for benchmarking when there is a large amount of previous data available.

The most common method used in the literature is the OLS, as it is intuitive to use; it can be carried out in most spreadsheet based systems. Various values from the literature were compiled to design a table of building types against energy intensity, where the energy intensity values are recorded in MJ/m^2[23]. However, we are not provided with a definition for the space floor area used in the calculations. Following the presentation of the above benchmarking methodologies, the paper concludes that these are further divided into two types: public and internal. Chung's study does not incorporate data originating from organizations such as CIBSE and ASHRAE. This would help in proving the differences between benchmarking techniques and values.

One needs to be careful when interpreting data values for electricity/energy consumption, as there is no standard way of calculation. Some authors [3] use the sales floor area of the shop, while others [12] use net floor area. Other authors, for instance [24] used multiple regression analysis during the benchmarking process. Using this method, the opening hours of the store are taken into account, as well as climate factors and building age. In some cases total energy consumption for a year is used; other authors use the average weekly consumption of stores for a year.

A.2.4 Tesco Benchmarks and energy consumption

Tesco has installed sub-meters to most of its stores aiming to reduce their energy consumption. This sub-metering scheme covers approximately 70% of the whole estate, while a third-party company collects the data. Table A.3 presents the average energy consumption of stores for the past 7 years, dividing them into the separated types. It illustrates that benchmarks published by various bodies are optimistic but achievable, especially in larger stores. Homeplus[5] stores have no refrigeration packs installed and it is interesting that they consume close to the published benchmarks for an office building.

In Figure A.1 the consumption of each type of store is presented in kWh/m^2. It shows the difference in consumption per square meter for each store type within the Tesco estate. It is apparent that as the store gets smaller, its electricity consumption per square metre increases. One reason could be that smaller stores (Express and some Metros) are electrically heated. Tassou [3] suggest that the balance between refrigerated/frozen and ambient products is an important factor that influences and justifies the higher energy intensity of smaller stores.

A.2.5 Analysis and prediction techniques

The ability to analyse and accurately forecast future events is currently becoming increasingly important, as most companies need to comply with the regulations mentioned in Section A.2.1. In addition to these, companies need to be able to analyse, forecast and reduce buildings' energy consumption as the electricity and gas prices are on an increasing trend.

[5] Homeplus is a relatively new store type for Tesco, these stores do not stock any refrigerated products.

Store Type	*2004-05 (kWh/m²)*	*2005-06 (kWh/m²)*	*2006-07 (kWh/m²)*	*2007-08 (kWh/m²)*	*2008-09 (kWh/m²)*	*2009-10 (kWh/m²)*	*2010-11 (kWh/m²)*
Express	1640	1483	1416	1327	1271	1220	1136
Metro	1086	1063	1024	980	929	851	806
Superstores North	1024	974	924	879	817	728	688
Superstores South	1131	1103	1047	1002	918	823	778
Extra	784	778	761	744	683	599	565
Homeplus	-	-	386	319	280	241	224

Table A.3: Energy Consumption across different store types in kWh/m^2

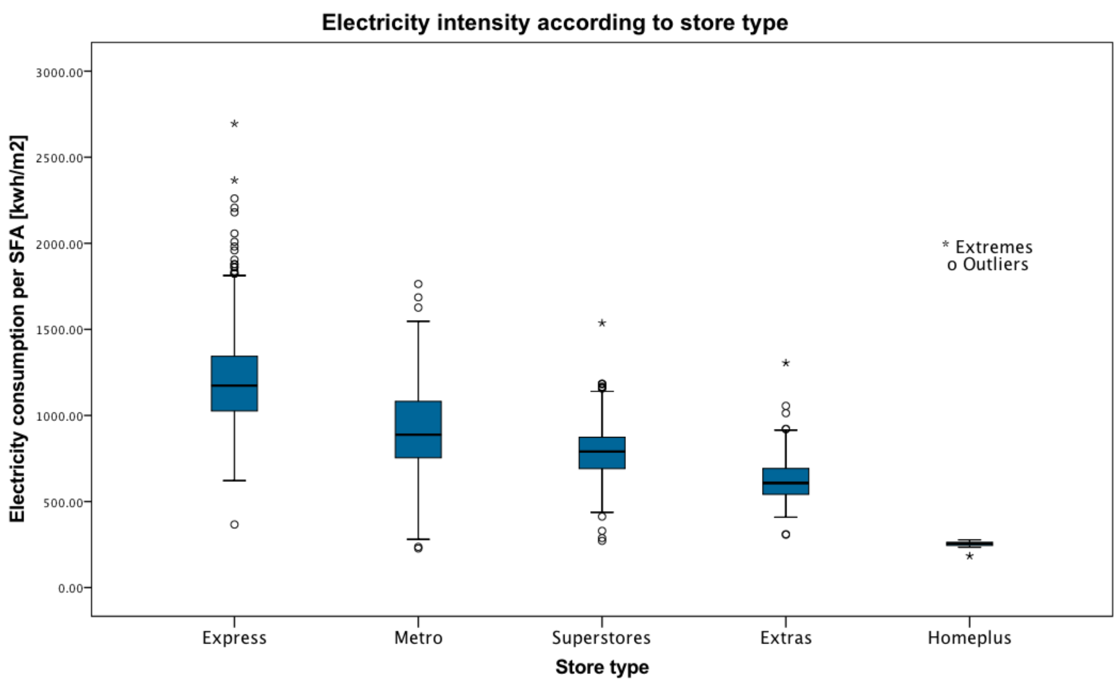

Figure A.1: Energy Consumption of Buildings in the Tesco estate

There are various methods mentioned in the literature for analysing and forecasting energy consumption; for example Tassou et. al. [3] reviewed the electricity consumption data of 2570 retail food stores in the UK, most of them owned by the major retailers. The paper presents an analysis of electricity consumption against sales floor area, in terms of average values for each category and standard deviations. It proposes an equation relating electrical energy consumption per sales area, W_e, to the sales area, A_s, as follows:

$$W_e = 3600\text{x}A_s^{-0.18} \tag{A.1}$$

Once validated such an equation would be of great value to the food retail sector; as one of the challenges that retailers come to face is the ability to predict the energy consumption of new buildings. It is therefore of some concern that Equation (A.1) does not take into account the geographical position of the store, or the construction materials.

In an attempt to validate Equation (A.1) the authors have plotted similar data to that presented in the work of Tassou [3] (Figure A.2), showing that currently, Tesco stores have less energy intensity per SFA than the average stores in the UK in 2006-07.

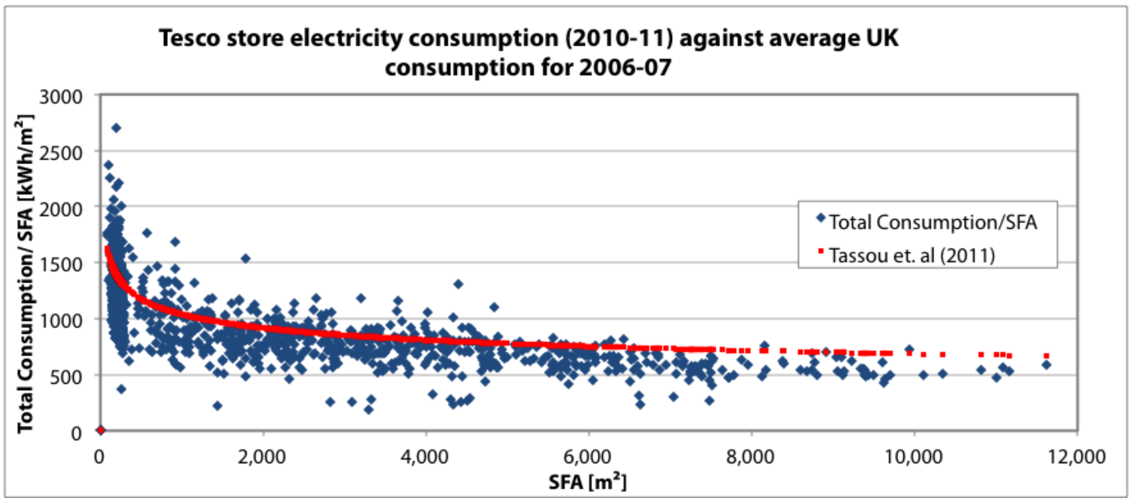

Figure A.2: Electricity consumption of Tesco stores and the average UK consumption in 2006-07.

Artificial Neural Networks Artificial Neural Networks (ANNs) are considered to be a modern forecasting tool. Firstly created for pattern recognition, ANNs have since developed into a powerful forecasting technique. Datta and Tassou [25] demonstrated that if trained using actual measured data, ANNs could be more reliable than Multiple Linear Regression (MLR) and Multiple Polynomial Regression (MPR). A monitoring system was installed, which logged the:

"Temperature and relative humidity of the store,

External air temperature and humidity,

Total electrical power consumption, of the store,

Electrical power consumption of refrigeration packs,

Gas consumption and underfloor heating flow and return temperatures".

A simple three-layered feed-forward neural network (NN) was then used. In order to evaluate factors that would affect the final result the most, the networks were trained using seven different configurations, modifying the input parameters and the number of time steps. The work arrived at the conclusion that the most important parameter is the time of day. The number of time steps used is not mentioned making it difficult to assess the accuracy of these results, as the performance of ANNs over longer periods of time is unknown.

Kalogirou [26] published a very comprehensive review of ANNs in renewable energy systems applications. This work explains the theory behind ANNs describing the principles that govern them and illustrating the parameter selection; it guides the reader through the whole process of building, training, testing and finally using ANNs for forecasting, warning the reader, where relevant, for common time-wasting mistakes. Various applications of ANNs are also presented, mostly in renewable energy systems. Additionally applications of ANNs in other energy systems are presented, including energy consumption prediction in commercial buildings, energy consumption optimization and forecasting of energy consumption. This work concludes that ANNs should not be underestimated as they do offer an alternative forecasting method.

A.2.6 Forecasting methodologies in the retail sector

In a private communication with J. Bruneel (R&D Software Team Leader at EnergyICT) it was stated that a combination of ANNs and MLR is used for the forecasting needs of the retail industry in the UK; a rather complex combination compared to the ones presented earlier in this work. Bruneel clarified that the system comprises of three different forecasts, a short term one (ANNs), able to forecast up to eight days in advance, a medium term one (MLR), able to forecast up to four months, and a long term one (MLR) that covers twelve months. Incorporated into those forecasts are eight different models, including every day of the week, plus one extra day for bank holidays. A back-propagation algorithm is used for the ANNs' training along with an optimization technique, Principle Component Analysis (PCA), in order to compress the 24 inputs for each day to 5. Reverse PCA is applied at the end of each round to retrieve the initial 24 outputs. Weather data from 200 weather stations across the UK are also used - these are monitored half-hourly with parameters including ambient temperature, sunshine, wind speed and humidity.

A.2.7 Forecasting Techniques within Tesco

In order to produce energy budgets for the year ahead. These budgets need to be accurate at store level as they are used by the business for goal setting and motivation.

This budgeting process divides the stores into their store director groups (SD), the store type and region of the country are taken into account, forming the grouping recognised and used by the business as a whole. Seasonality profiles are then created for each SD group.

In order to create the seasonality profile for each group, a selection process takes place, which includes five years worth of electricity consumption data for each store, but excludes stores that:

- Do not have complete data sets for that specific year.
- Are electrically heated (these are not entirely excluded; specific profiles are created for them).

- Have a weekly consumption at the beginning of the year, which was more than 10% different to the weekly consumption at the end of the year. This difference is usually because there were projects undertaken on that store that changed its consumption, for which the model does not have the ability to predict. Projects include changing the square footage of the store or 'refreshing' the store by installing new, more efficient equipment. This is to provide a flat or as close to business as usual profile, removing the effect of energy initiatives but also operational changes.

Taking into account all of the information, the remaining values are used to calculate how far above or below average the consumption was in each of the 52 weeks of the year; the seasonality profile is then created by calculating the average for each group of stores. Smoothing then takes place, which averages every three weeks, followed by a check to make sure that the Christmas period falls on the right Tesco week.

Subsequently, the team selects six weeks as close as possible to the end of the year, removing any weeks with extreme temperatures. The weeks are then divided by the seasonality expected for those weeks to get an *absolute average* value.

The *absolute average* value is then multiplied by the seasonality profile of each group to create a forecast weekly consumption value. Even though this method cannot be statistically verified, this is the best way of forecasting for Tesco, as the electricity consumption is never very close to an average value, mainly due to the effect of temperature changes.

A.3 Methods

As mentioned in Section A.2.4, sub-metering was installed into approximately 70% of the buildings in the estate. For the purpose of this work, weekly electricity data for the period of 1/3/2010-1/3/11 were obtained through the data collection contractor. These dates were chosen as they form the latest Tesco year (2010-11). The values were then quality checked and verified.

The first action taken was to add the CHP generation values to the MPAN data. Later, the set was checked for missing values. Any stores that did not have valid 52 weeks worth of data were eliminated. This eliminated stores that were built in the year 2010-11, as well as stores with sub-metering issues. Stores that were extended/reduced in SFA within the year were also excluded, as these would have brought inaccuracies in the calculations. Another quality measure was the availability of SFA data for the store. If the SFA was not present for the 2010-11 period the store was excluded as well.

Following these quality control checks, the number of stores included in the study was still significant; data used from 1518 out of a total of 2123 stores.

Gas consumption is not as highly sub-metered therefore after the quality checks, 411 stores were included out of approximately 900 stores that are gas-heated.

A.4 Results

A.4.1 Impact of weather

It is widely known that outside air temperature affects the energy consumption of buildings. However, each building is different and may behave differently under distinctive circumstances. It is clear that when temperature deviates from the average, the electricity consumption of stores increases. This increase is due to the heating load during the winter (in electrically heated stores) and due to the heavier cooling load and refrigeration during the summer.

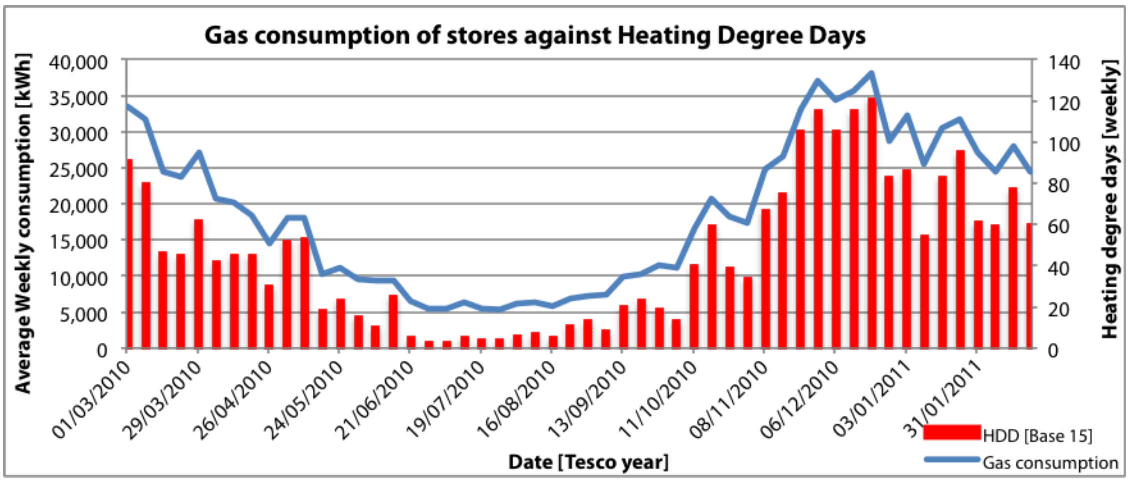

Figure A.3: Gas consumption affected by heating degree-days.

The effect of temperature on energy consumption is more obvious when plotting the average weekly energy consumption in kWh against Heating Degree-Days [HDD] for the same period. For Figures A.3 and A.4 the HDD and Cooling Degree days (CDD) were obtained from [27], for the period between 1/3/2010 and 1/3/2011, using a base temperature of 15°C. Figure A.3 shows how the gas consumption is affected by outside air temperature. Undoubtedly it is affected by the weather, as the two profiles follow each other every week.

As shown in Figure A.4, the heavier electricity consumption during summer can be explained by the cooling load needed. This consists of the electricity needed to keep the stores cold, as well as the electricity needed for refrigeration. During the winter the electricity consumption is still high, as the smaller stores are electrically heated. The significant increase in consumption noted around December can be explained by the increased amount of sales that take place in the stores due to the Christmas period.

A.4.2 Other factors that affect electricity consumption

As mentioned earlier, weather is not the only factor that affects the energy consumption of retail stores. In an attempt to find other factors that have an effect the authors have investigated, amongst others, the effect of the geographical location of the store that was found to have a

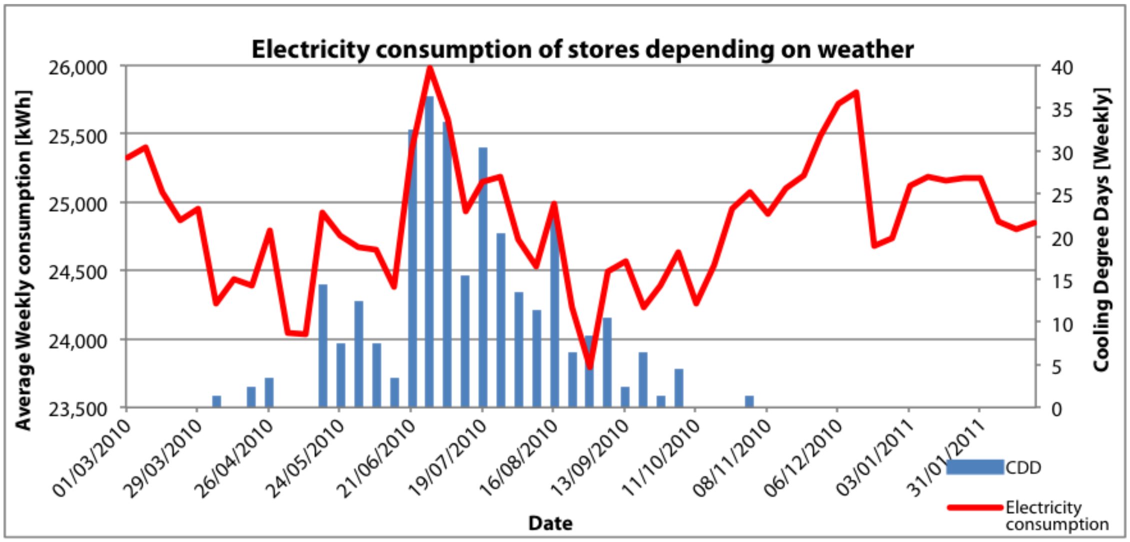

Figure A.4: The electricity consumption against cooling degree-days.

minor impact compared to the other factors. Factors that need further investigation include day-of-the-week, Section A.4.2.1, sales, Section A.4.2.2, opening hours and customer volume.

Day-of-the-week

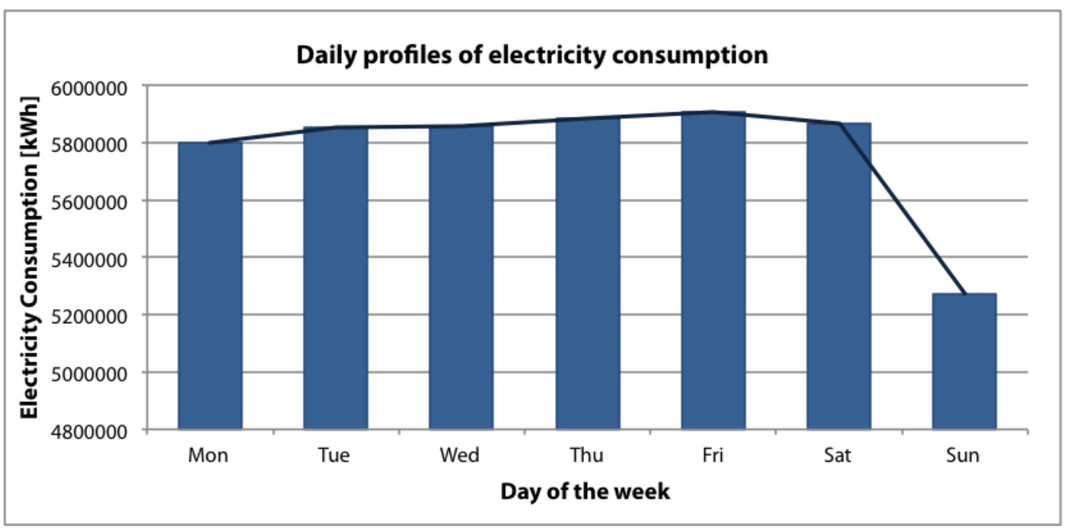

Figure A.5: The effect of the day of the week on electricity consumption.

Figure A.5 indicates that the day-of-the-week is an important factor affecting the energy consumption. It has been observed that on Friday and Saturday stores always consume more electricity than the rest of the week. Trading hours on a Saturday are less than trading hours on weekdays; the difference in energy consumption is apparent nonetheless. This could possibly be explained by the number of customers entering the stores during the weekend and the number of sales/pounds spent in store (usually linked with refrigeration doors opening and closing more often, with customers taking products off the shelves, and staff refilling the shelves), but more information is needed to confirm this.

Sales

At first glance, Figure A.6 shows a good correlation of electricity consumption with sales. However, a closer look at the individual store types reveals less correlation. This is especially apparent in Express stores as their energy intensity breadth is higher than any other store type.

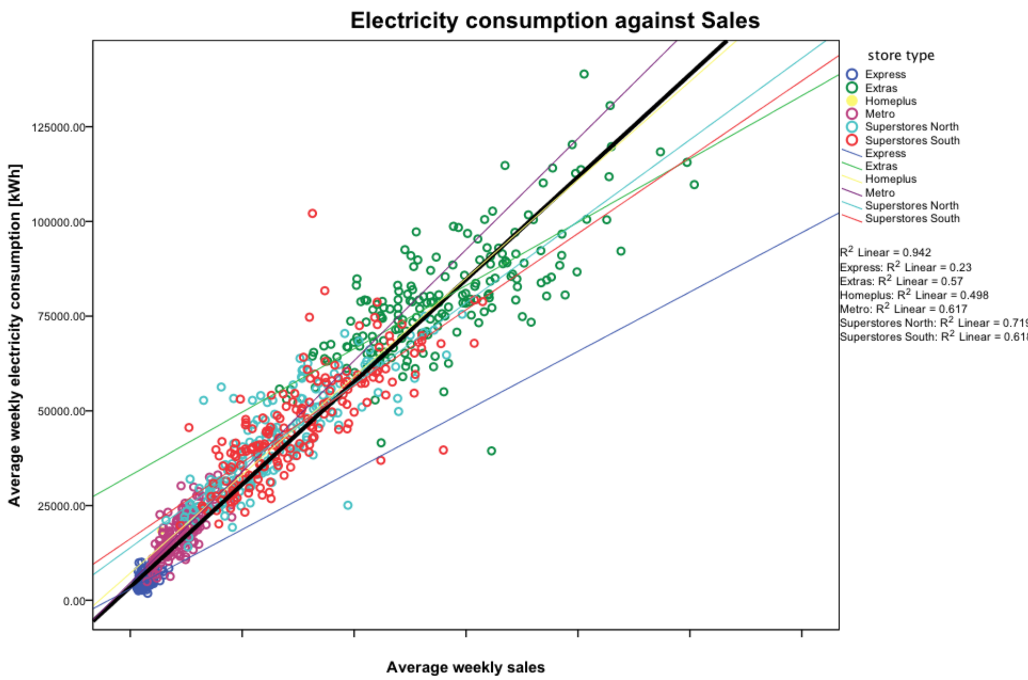

Figure A.6: Weekly electricity consumption against sales.

Figure A.7 presents the electricity consumption of extra stores. It is interesting that stores of the same type, and same size consume different amounts of electricity when their sales volume is different.

Store build date.

Another factor that is important to consider is the age of the building. Tesco design standards have been changing over the years, altering both the building materials and the equipment used within a store. Building regulations have also changed significantly since the first Tesco store was built in 1929 [28].

The influence of changes in building regulations can be seen in Figure A.8 but this is not clear. The box plot shows how the electricity consumption per square metre varies with built

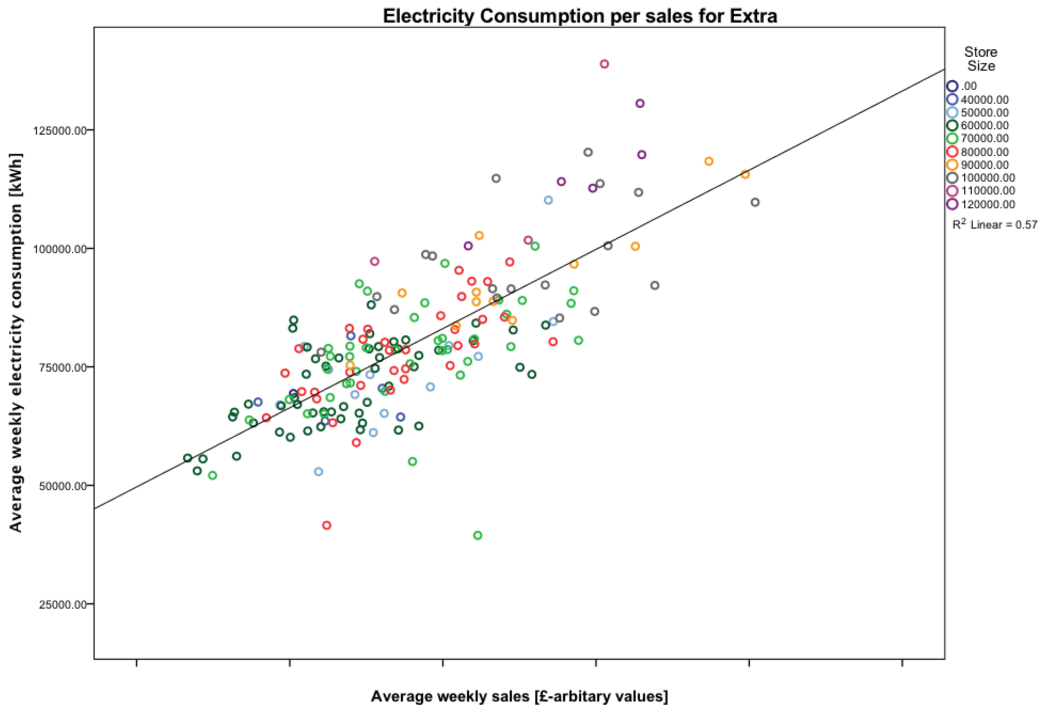

Figure A.7: Electricity consumption against sales for Extras.

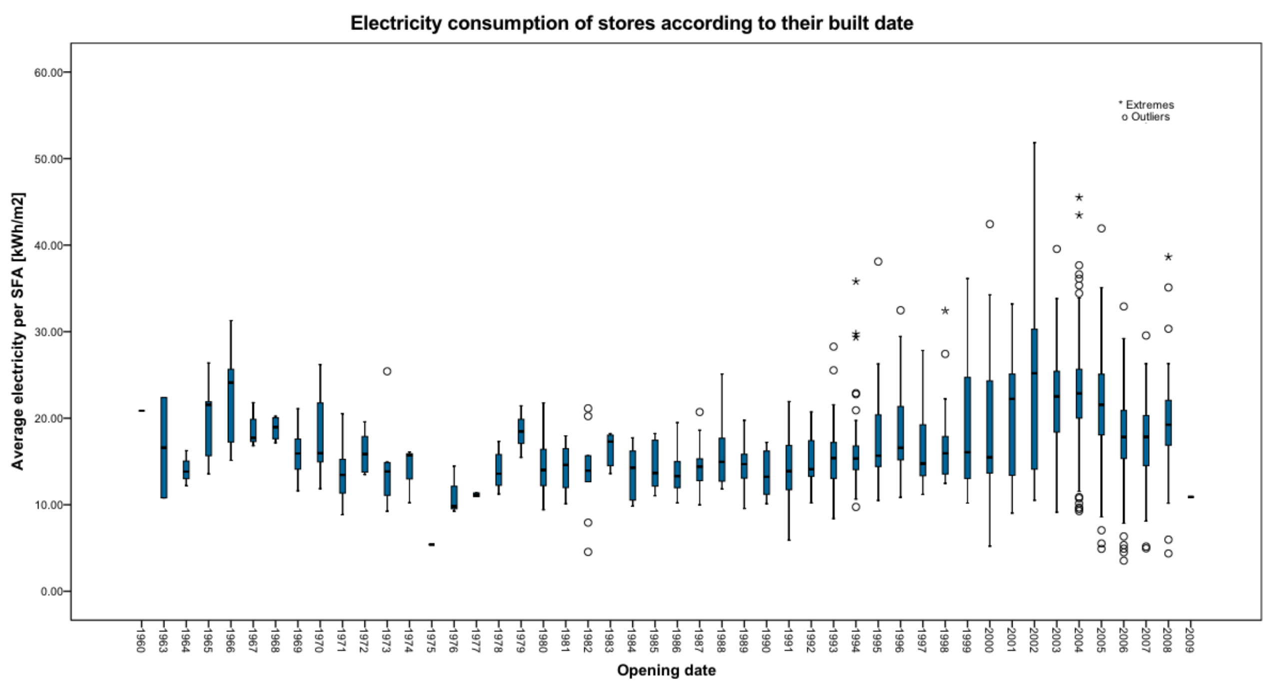

Figure A.8: Does build date affect the behaviour of the building?

date. There is an apparent dip in the energy consumption of the buildings built in the 1970s, during the economic/oil crisis, possibly due to the 1972 *Conservation of fuel and power provisions for dwellings* [29].This is followed by an overall increase in consumption of buildings built around the 80s. Until 1996 the behaviour is fairly consistent, and then there is another dip, probably caused by the building regulations in 1996, and again after 2002 and 2005. The increase after the millennium can be explained by the strategic increase in the number of Express stores being built by Tesco in that decade. As shown earlier in figure 1, Express stores have higher electricity consumption per m^2 than the other store types.

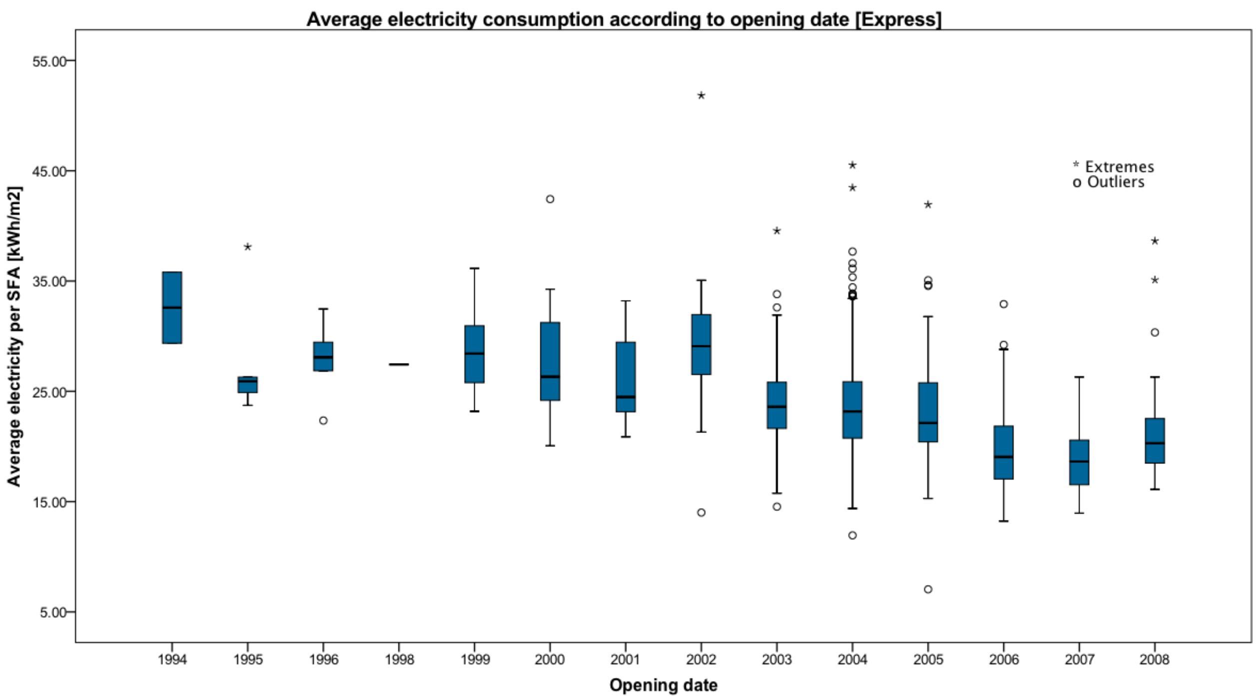

Figure A.9: Electricity consumption of Express stores according to their built date.

Figure A.9 presents the electricity consumption per SFA for the Express stores, according to their built date. One can see the step change (reduction) of electricity consumption between stores built before 2002 and stores built after 2002. The effect of building regulations is more apparent in the behaviour of Express stores due to the electrical heating.

It is not expected that the electrical behaviour of the remaining store types will be affected by the building regulations, as these stores are heated by gas. There is, however, still an interesting change in their behaviour illustrated by Figure A.10. This can be explained by the changes in design standards within the company, affecting: the number and type of fridge/ freezer cabinets installed in stores, the type and amount of lighting installed, as well as the type and amount of other equipment.

Further investigation into the electricity behaviour of the buildings according to their build year is required as this might indicate contractors or equipment types that drive the energy consumption.

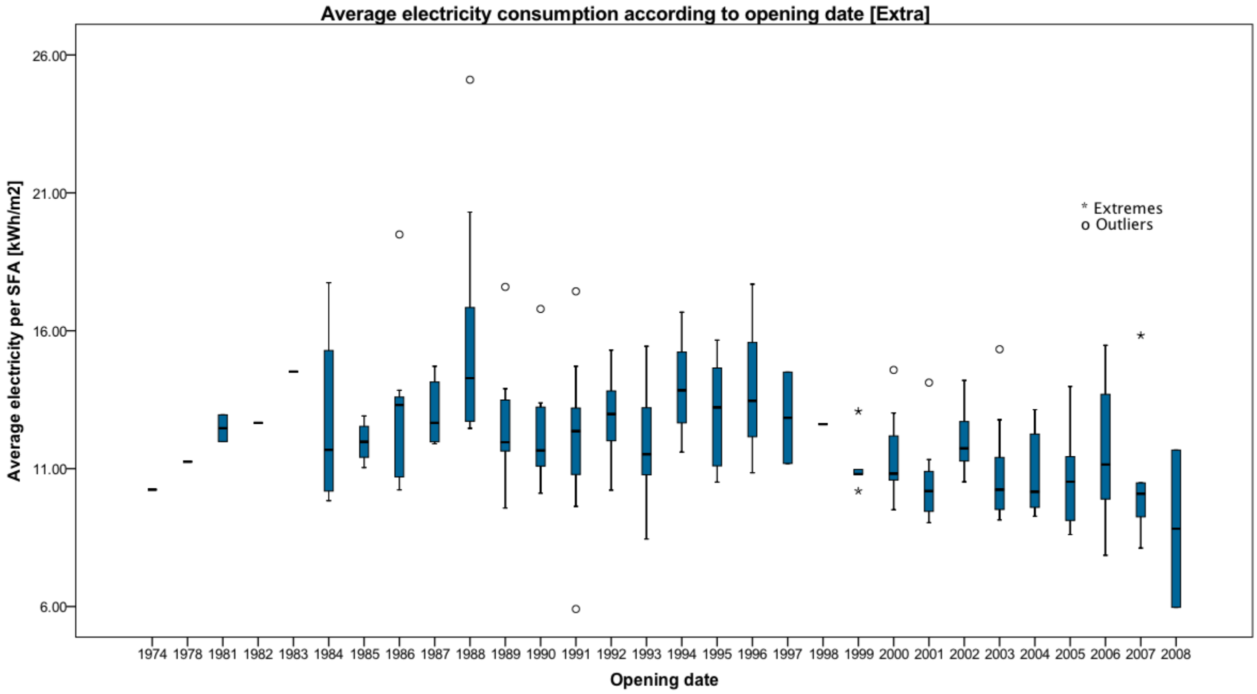

Figure A.10: Electricity consumption of Extra stores according to their built date.

Human behaviour

The energy consumption of buildings does not only depend on the aforementioned factors. Human behaviour has an important role as well; surely the efficiency of equipment is limited by the end user. No matter how efficient refrigeration is, if doors are left open, packs will consume more than expected. If staff in store overrides lighting schedules, lighting will consume more than expected. If staff switches on ovens before the set time to preheat them, the ovens will consume more than expected. Consequently, one needs to look closer at how human behaviour affects the energy consumption of stores. This will form part of future work.

A.5 Conclusions and future work

This work has described the current state of the retail industry in terms of energy consumption and efficiency. It has presented various benchmark values for the consumption of retail buildings; ranging from 505 kWh/m^2 to 955 kWh/m^2 depending on the organization publishing the values. It has also shown the different units these are quoted in and the breadth of techniques used in their calculations. These results indicate that benchmarking the energy consumption of buildings is not an easy task; new and more uniform ways of calculating benchmarks are needed.

Retail buildings in the Tesco estate were found to have energy consumption values between 230 kWh/m^2 and 2000 kWh/m^{2}per year. Still the average consumption of these buildings in

2010-11 was found to be less than the calculated UK average of the 2006-07 period.

The effect of weather on gas and electricity consumption was stated, as well as the effect of the day-of-the-week. Sales volume was also indicated as a factor affecting the electricity consumption along with the built date of the building. It was identified that human behaviour is an important factor and needs to be investigated further.

Gaps in the industry were also identified, such as the lack of energy prediction tools available to the energy professionals. Benchmarking and best practise guides can be too optimistic when compared to actual energy consumption figures, CIBSE 505 kWh/m^2, ASHRAE 565-710 kWh/m^2, compared to an average of 806 kWh/m^2 consumed by a Tesco Metro store. Spreadsheet models used by Tesco are accurate to 5% when averaged for the whole estate, but are not always accurate to store level. Even though the forecasting ability of Artificial Neural Networks cannot be undervalued, these have not been demonstrated to produce accurate results for prolonged periods of time.

The above lead to the conclusion that the sector needs to move towards more sophisticated techniques in forecasting the energy consumption of its buildings. These should incorporate the various factors affecting the energy consumption, including but not limited to: HDD and CDD, sales figures, built date and day-of-the-week profiles.

Future work will include the investigation of other factors that affect the energy consumption of retail buildings. These factors should contain the building materials used, the type of equipment installed in the building and the operating hours of the store, as well as the operational behaviour of the staff and any other factors that might arise.

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Appendix B: Paper 2

Reference:

Spyrou, M. S., Shanks, K., Cook, M. J., Pitcher, J., & Lee, R. (2014). An empirical study of electricity and gas demand drivers in large food retail buildings of a national organisation. Energy and Buildings, 68, 172182. doi:10.1016/j.enbuild.2013.09.015

An empirical study of electricity and gas demand drivers in food retail buildings

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Abstract

Food retail buildings account for a measurable proportion of a country's energy consumption and resultant carbon emissions where energy demands are also a manageable component of business operating costs. Increasing understanding of the drivers of end-use energy demands in this sector can enable the development of effective benchmarking systems to underpin energy management tools and aid identification and evaluation of interventions to reduce operational energy demand. Whilst there are a number of theoretical and semi-empirical benchmarking and thermal modelling tools that can be used for food retail building stocks, these do not readily account for the variance of technical and non-technical factors that can influence end-use demands.

This paper discusses the various drivers of energy end-uses of typical UK food retail stores. It reports on an empirical study of one organisation's national food retail building stock to evaluate the influence of various factors on annual store electricity and gas demands. Multiple regression models are discussed in the context of the development and application of a methodology for estimating annual energy end-use demand in food retail buildings. The established models for electricity and gas demand (for stores with and without CHP) account for 75%, 50% and 77% of the variation, respectively.

B.1 Introduction

Currently in the UK there are more than 9,000 food retail stores with sales floor areas of more than 280 m^2. Most of these stores are operated by the four largest supermarket multiples: Tesco (29.7%), ASDA (17.7%), Sainsbury's (17.0%) and Morrisons (11.8%) [1, 2]. The remaining 23.8% are shared by smaller chains such as Waitrose and Iceland [2]. The energy consumption of these stores is important for the profitability of their organisation as their operating margins are generally low at an average of 4.2% in 2005 [3]. Additionally the consumption is important for national CO^2 emission targets where the food retail sector accounts for more than 3% of the total electricity consumption in the UK and approximately 1% of total UK CO^2 emissions [4].

Table B.1: Retail store categories

Category	Sales floor area [m^2]
Convenience store	$<$280
Supermarket	280 $-$ 1,400
Superstore	1,400 $-$ 5,750
Hypermarket	$>$5,750

Considering both these issues, along with the relative homogeneity of management structures and energy end-uses in food retail organisations, minimising and managing energy demand is an important opportunity for both business competitiveness and national targets.

Strategic financial planning in the sector's large organisations typically take account of future demands for gas and electricity. Future demands and financial implications are estimated for different time frames, such as the year ahead or future months, and account for increasing energy prices, changes in store sizes and reductions due to investment in energy efficiency initiatives applied across an organisation's building stock. Projected energy demands are used for multiple purposes including the identification of how efficiently individual stores are operating, indicating generally where inefficiencies lie and when faults occur. With such multiple purposes and scope of applications, the energy demand tools developed to estimate future demands need to be able to provide insights on many technical and non-technical factors that influence gas and electricity demand. The aim of this study is to identify and interpret the implications of key factors influencing aggregated annual electricity and gas demand, in a sample of food retail stores, to inform the further development of new energy budgeting and management tools for a large food retail organisation.

Related studies reported in the literature tend to focus on detailed levels of analysis and factors to establish causal links with end-use demands, for example [5, 6, 7, 8]. This study backtracks somewhat to investigate demands and drivers at the aggregated annual level. In doing this, causal links are suggested where their relative significance is evaluated in the context of the range of functions of such models.

The organisation's retail building stock studied here is comprised of four different store formats, which can be aligned with the common categories based on sales floor areas as shown in Table B.1 [9].

Whilst there is a high degree of heterogeneity across the store categories, this reduces when inspecting the stock within each category. Store formats differ in terms of size, location, proportion of total floor area for different functions (e.g. frozen food, non-food, home delivery, back office, stores, etc.), external lighting provision, in-store services (e.g. in-store bakery, fish/ meat/ delicatessen counters), opening times, building type (e.g. new build, redevelopment from previous different use) and on-site services (e.g. petrol station, car wash, home delivery, click and collect). As a result of these differences the composition and intensity of energy end-uses varies across the store categories but have comparatively less within each category. Convenience stores are the most common category of stores in the organisation's stock, numbering more than 2,000 (more than 50% of the total stock) [10]. They are usually found close to the consumer; either located within a town centre, close to apartment blocks, or as part of petrol filling stations. Their product ranges, and thereby also in-store services, depend on the local market demand. They are typically closely related to their location in urban centres and are mostly chilled-food dominated as they bring the classic lunch meal to their customers. These stores are electrically heated. Supermarkets are the most individual store category. These stores are usually found within town centres and the building types vary from new, purpose built stores to refurbished buildings such as churches. Similar to superstores these stores include a mixture of in-store services, depending on their location and market demands. Typically they have an in-store bakery but not any fish, meat or delicatessen counters and are a mixture of gas and electrical heating with some having a small number (i.e. one or two) ceiling mounted, cassette type cold air recirculating units for local cooling. Superstores are the second most common store category, and are found closer to the consumer, usually at the edge of the town centre, and are typically built for purpose. In rare cases some of these stores were acquired from previous owners and refurbished to meet the organisation's design standards. These stores include a mixture of in-store and on-site services, as well as a mixture of construction types, as they can be timber framed, or simple steel framed retail sheds. The majority of these stores are heated by a central gas system, and approximately 15% of them have a Combined Heat and Power (CHP) plant. Cooling is provided by centralised constant volume air conditioning systems. Hypermarkets are the largest retail stores within the studied stock. These are usually located outside town centres - normally at the edge of the town- and are designed for purpose, thereby maintaining the organisation's and national building standards at the time of construction. Being the largest stores of the stock, they contain the full range of in-store and on-site services, such as petrol filling station, in-store bakery, fish; meat & delicatessen counters as well as significant non-food sales area, including clothing departments and electronics departments. Although all hypermarkets have similar product lines, the proportional composition of these varies. In general, these stores have similar on-site electrical and gas end-uses; therefore have a lower relative variance in average electricity and gas intensity. Approximately 75% of all hypermarkets are open 24 hours a day. The majority of these stores are heated by a central gas fired low temperature hot water (LTHW) system with 15% having a CHP engine installed that generates electricity and heat. Cooling is provided by centralised constant volume air conditioning systems with vapour compression chillers.

This study is the first stage of a larger project which seeks to develop an energy forecasting tool for the organisation's entire stock of food retail stores. Due to this and the characteristics mentioned above, hypermarkets were selected as the study sample. The energy demand of hypermarkets will be discussed further in section B.2, while data and analysis methods are explained in section B.3. Results are presented and discussed in section B.4. Section B.5 concludes the work.

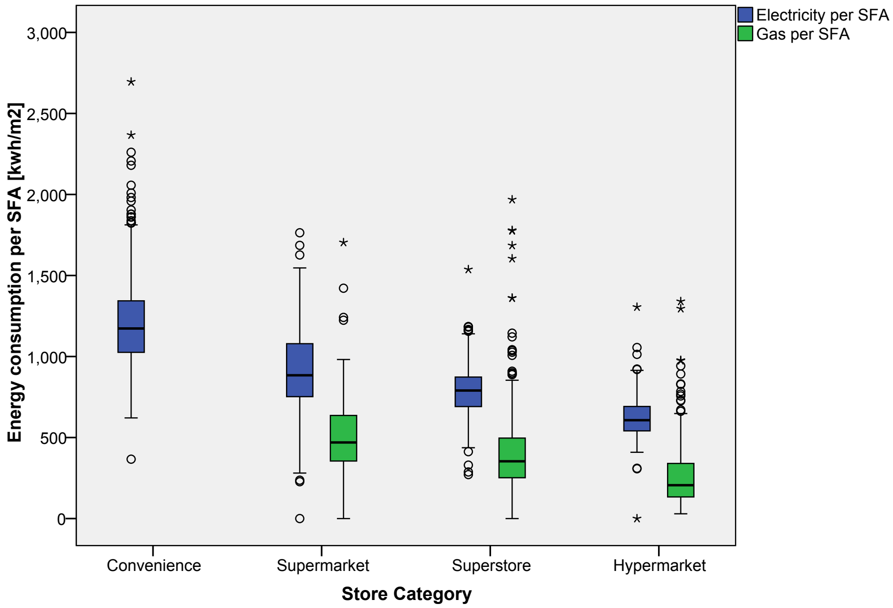

Figure B.1: Electricity and Gas intensity of for each store category

B.2 Energy demand in food retail stores

The energy end-use demand of food retail stores is usually met by a combination of electricity and gas. A sizeable body of work has been developed in the literature on electricity demands in food retail stores but much less has been reported on gas-fuelled end-uses. Typically gas accounts for a 20% of the total energy demand in hypermarkets as shown in Figure B.2.

B.2.1 Electricity

Electricity typically accounts for more than 70% of the energy consumed in UK supermarkets [4], and for approximately 80% in the study sample. An average hypermarket consumes 4.1GWh of electricity per year. The main end-uses include refrigeration, Heating Ventilation and Air-Conditioning (HVAC), lighting, and other general e.g socket outlets, cash registers, and specialist in-store services such as bakeries or large kitchens serving either customer or staff restaurants. The percentage contribution of each end-use depends on the range and relative magnitude of end-uses present in a store. For example, Tassou et al. [4] report that refrigeration accounts for 29% of electricity demand in a hypermarket that contained a customer restaurant and a bakery, whereas refrigeration accounting for over 50% of electricity in modern supermarkets has also been evidenced [11]. Whilst refrigeration is typically reported as being the largest energy end-use in all store categories, other electrical end-uses can be significant.

B.2.1.1 Refrigeration

Most large retail stores provide chilled and frozen products in display cases held at high (3 to 5°C) and low (-18 to -22 °C) temperature. The condenser and compressor elements of the refrigerant circuits are located away from the sales floor area, either in an enclosed plant room or in the open outdoors. This ensures that heat taken out of the circuits does not add unnecessary heat gains to the chilled or frozen food sales areas. The evaporator elements are built into the chilled or frozen display cases in the sales areas.

The load on refrigeration circuits for chilled and frozen cases is mainly driven by conditions of the local thermal environment at both evaporators and condensers. At evaporators, i.e. chilled or frozen food cases in sales areas, heat is gained from the local environment around cases through radiative, convective and conductive heat transfer [12, 13]. At the condenser elements, the rate of heat taken out of the refrigerant circuit is a function of the temperature difference between the refrigerant entering the condenser and the local ambient air temperature, and the rate of airflow, driven by condenser fans, across the condenser heat exchanger. The amount of heat gained is influenced by usage in terms of how often customers remove products and staff restock cases. During these actions the amount of warmer air circulating into a case increases thereby increasing, albeit to a small extent, the load on the refrigeration circuit. As the local ambient temperature increases the amount of heat taken out of the refrigerant decreases, which increases either the number of condenser fans running or increases the load on the compressor.

Refrigeration load has also been shown to be influenced by relative humidity which affects both overall refrigeration loads [14] and more specifically the electrical demands on anti-sweat heaters and defrost cycles [15]. As low temperature systems, for frozen food, typically consume more electricity than high temperature systems, for chilled food, the mix/ratio of low temperature to high temperature cases influences the total refrigeration load of a store [4].

Overall the interdependence between each element of low and high temperature refrigeration systems means that a rise in external temperature can affect refrigeration electrical loads. At evaporators, this is through increased local temperatures around cases in sales areas and usage patterns; at condensers, it is through condenser fans having to provide increased air flow rates over condenser heat exchangers; and at compressors, it is because greater work is needed to condition the refrigerant to the required level for return to the evaporators.

Chilled food cases also incorporate lighting and circulation fans, which are a comparatively small component of the total electrical demand for refrigeration systems. At an aggregated level, total electrical energy demand for individual cases has been found to be correlated with the total display area of individual cases [16].

B.2.1.2 Heating, Ventilation and Air Conditioning

Heating, ventilation and air conditioning in food retail buildings provides thermal comfort for customers and staff. Conditions necessary for products that are sensitive to temperature and humidity are maintained within separate dedicated conditioned spaces, such as cold rooms and refrigerated display cases. As stores are effectively large open plan boxes, giving maximum flexibility of space use to the retailer, large-scale convection heating and cooling is provided by centralised air systems. These centralised air systems provide heating and cooling to sales floor areas. In the sample studied, all heating and cooling is provided to the sales floor area via bespoke packaged air handling units (AHUs). These units have a fan section and mixing box, a heating coil and a cooling coil with dedicated condenser and compressors as part of the air-handling package. The fan is fixed speed, and the mixing box has dampers set to constantly provide a fixed ratio of 1:3, fresh air to re-circulated air, in order to meet the ventilation guidelines for supermarkets [17]. The air-handling units distribute conditioned air via high-level ductwork to sales floor areas. AHU heating coils are serviced by LTHW from a gas fired boiler circuit, thereby being a component of the overall gas demand. Where the store has a CHP installed, the CHP is the lead boiler in the LTHW circuit. The air-handling units temper incoming fresh air by mixing it with warm stratified air. The amount of heat added to the supplied air is modulated through the heating coil to ensure sales floor area temperature set points are maintained. AHU cooling coils are direct expansion circuits operating on a conventional vapour-compression refrigeration cycle, thereby being a component of the overall electricity demand. To supply cooling to the sales floor areas, the mix of fresh and re-circulated air is passed over the cooling coil, in which the refrigerant temperature is modulated as a function of the amount of cooling needed. To minimise the cooling demand of cooling coils, cold air is extracted from the refrigerated aisles via an extract path underneath the refrigerated cabinets. This cool air is returned to one of the AHUs and mixed with incoming fresh air. In order to prevent ingress of cold outdoor air around entrance areas, warm air curtains are used at the main entrance and warehouse doors of each store. The heating for these is provided by either the LTHW circuit, thereby being part of the gas demand, or via electric heaters, thereby being part of the electricity demand. Temperature set-points for heating and cooling are set remotely (19°C in the heating season and 24 °C in the cooling season), in accordance with recommended levels by CIBSE Guide A [18] and follow a company-wide strategy, therefore it is assumed that all stores are maintained at the same internal temperature.

B.2.1.3 Lighting

Lighting includes in-store lighting, lighting for the back offices and storerooms, as well as for perimeters and car parks. Lighting is controlled so that certain lux levels are met during the main opening hours: 8am to 10pm. Lux levels are then reduced between 10pm and 8am in 24 hour stores. When stores are closed, stocking lighting is in place, which is significantly lower than the trading lux level. Lux levels are set according to the guidelines in [18].

In recently built stores there is a trend towards the control of some in-store lighting as a function of daylight conditions. In these situations lighting controls harness the daylight benefits of store designs whereby facades with large areas of glazing allow daylight to penetrate a portion of the sales areas. In these situations a number of rows of artificial lighting, close to glazed areas, are automatically controlled so that when minimum in-store lighting levels are met by daylight some rows are automatically dimmed. This modulation of artificial lighting provision can significantly offset the lighting load.

Specialist accent lighting is also increasingly used to differentiate particular products or enhance visual colouring and quality of fruit and vegetables in many stores. This involves the use of discharge lamps mounted in down lighters, operated during the main opening hours.

Such accent lighting is in addition to standard sales floor area lighting.

Lighting is also provided around the perimeter of stores and associated car parks following the BS5489-1.2003: Code ofpractice for the design of road lighting [19].

Whilst overall lighting is a significant component of total store energy demand, i.e. 17% on average, and a direct function of opening hours, the proportional influence is dependent on the store's format and use of automated daylight linked controls.

B.2.1.4 Specialist services

Stores of all scales have various specialist services, which can be defined as non-standard service or product lines. For example, some larger stores have customer restaurants whilst some smaller stores have customer coffee machines. The existence of these has an effect on comparing electricity demand, at an aggregated total store consumption level between stores of similar types. Specialist store services include:

- Customer restaurants
- Petrol stations
- Photographic printing
- Deli/meat/fish counters

B.2.1.5 Non-submetered consumption

Other electrical end-uses common in all stores are those that are required for the retail function, including check-outs; control and security systems; telecommunications; storage areas and small power outlets both on sales floor and in the back office areas are typically non-submetered. Equipment that would usually fall in any of the above categories, sections B.2.1.1-B.2.1.4, but have been replaced after the installation of submetering can also sometimes appear in the non-submetered category due to incorrect re-installation of metering.

B.2.2 Gas

As mentioned earlier, gas accounts for about 20% of the energy consumed in the study sample, an average hypermarket consumes 1.8 GWh of gas in a year. The main end-uses include heating and specialist in-store services such as bakeries and cooking facilities, but the percentage contribution of each end-use is not clear, as gas consumption of the study sample is not sub-metered.

B.2.2.1 Heating

Heating in the sample of hypermarkets studied is mainly provided by LTHW heating coils, as mentioned in section B.2.1.2 above, and is therefore part of the gas demand. In a proportion of the stores, heating from warm air curtains, located over store public entrances, is by centralised gas fired LTHW circuits. Whilst the heating energy demand of these is expected to be highly sensitive to outside air temperature the small amount of resultant gas demand is too small to be evident in a store's total aggregated annual gas consumption.

B.2.2.2 Cooking

Cooking and baking are the secondary uses of gas in most large stores. Cooking includes cooking of food for the employees in the employee canteen, the dinners in the customer restaurant, as well as cooking of ready-made foods, such as hot chicken and bakery products. Bakery products include fresh bread and other bakery and confectionery goods.

B.2.2.3 CHP

A number of stores have gas fired combined heat and power (CHP) systems which generate heat and electricity for use onsite. These systems are sized to meet a portion of the heat demand of a store and generate this as a by-product of generating electricity thus offsetting some of the electricity demand from the national network [20, 21]. The organisation uses a company-wide strategy for the operation of the plants therefore it is assumed that all CHP plants were operated under the same strategy during the year of data collection for this study. The CHP plants included in the sample use gas for the generation of electricity, it is therefore expected that these stores will consume more gas than the stores without a CHP system.

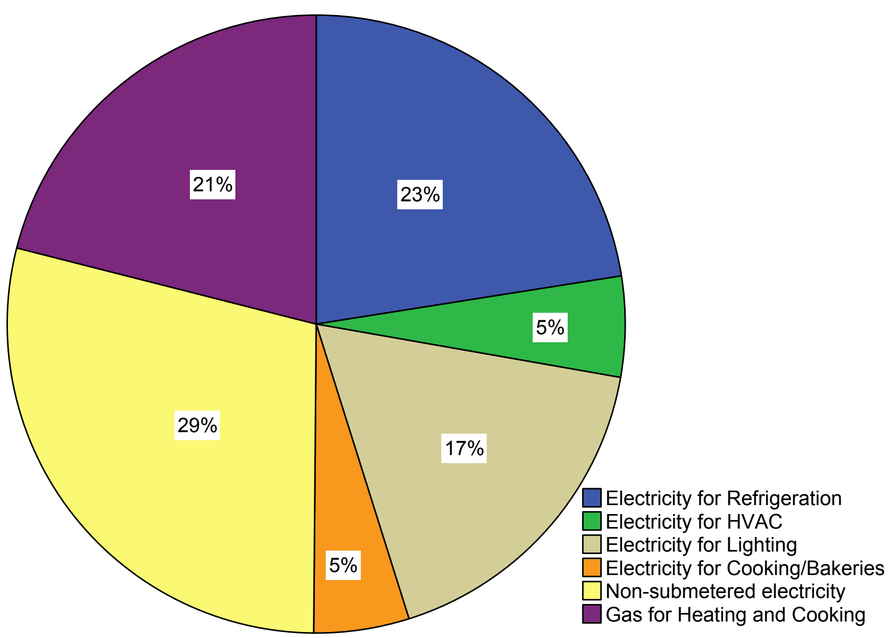

Figure B.2: Breakdown of average annual end-use demands in Hypermarkets.

B.3 Data and Analysis methods

B.3.1 Drivers of energy demand

In order to build a model to estimate energy demand, i.e. total annual electricity and total annual gas, the first step is to identify the factors that influence these demands at the aggregated level. Whilst these can be identified from theoretical concepts of energy performance and preliminary correlation tests, the availability of relevant data and information limits the factors that can be used to investigate what drives variation in these energy demands. This has implications for casual links between factors and end-use energy demands. It is assumed that the drivers of the various end-use energy demands described in Section B.2, will have a measurable influence on total electricity and gas demands. These end-use related drivers can be grouped into those that have constant physical characteristics, such as size and thermal performance, and those that represent the operational context of individual stores. A summary table of all factors is included in Table B.3.1.2.

B.3.1.1 Physical

In any building stock populated by one building type, such as the study sample of hypermarkets, store size would be expected to influence total electricity and gas demand, where the scale of the demand is more clearly a function of the overall size and the thermo-physical characteristics of the building envelope. Whilst store size, in terms of total floor area and sales floor area is readily available in centralised databases, the thermo-physical characteristics of envelope elements, i.e. surface areas; thermal conductance; solar transmission; orientation and exposure, are not. To overcome the absence of information and data on these primary drivers of heating and cooling the *Year of Construction* was identified as an indicator of energy related thermo-physical characteristics of a store's envelope, similar to what was used by Chung et. al. [5]. This is because even though energy related design regulations and the organisation's standards have changed over time for efficiency or architectural reasons, stores built within a year are very similar. The main step change in these regulations and standards occurred in 2002 when envelope energy related specifications were enforced by the organisation; new specifications required stores to have higher ceilings and be of steel frame and panel construction instead of brickwork. Because of this whether a store was built or refurbished before or after 2002 (*Pre-Post 2002*) was adopted as a dichotomous independent variable.

Additionally as the stores in the study sample all have centralised air systems, heating and cooling load is also a function of the amount of air that is heated or cooled, which can be represented by a store's volume, as discussed in [22]. As the volumes of conditioned spaces in each store were not readily available the assumption was adopted that store volume is an approximately linear function of ceiling height (*Ceiling Height)* and was therefore included. Ceiling height does not fully represent the volume of air in the stores, as some stores have mezzanine levels, therefore the *No of Trading Floors* was also included as a factor to investigate that relationship.

Although *Total Floor Area* defines the overall size of a store and therefore the scale of energy related end-uses, not all spaces in a store are conditioned therefore it is usual practice to account for sales floor area (*SFA*). SFA is usually considered to be half of the total floor area of a store [14, 12]. While the influence of floor area (total and sales) on total energy and energy intensity should differ it is also possible that energy intensity is an inverse function of floor areas as efficiencies of scale will provide a degree of efficiency.

It is expected that stores with a larger area for refrigeration cases will consume more electricity. As a variable to represent the ratio of refrigerated to ambient sales floor areas was not available, an indicative variable of *Food: Non-Food Ratio*, was adopted. This was selected because a number of food products usually need to be kept in cooled conditions. However, by way of example, electrical products are typically associated with electricity consuming TV walls.

As noted in section B.2.2.3 CHP plants are present in some of the studied sample and have the effect of increasing gas demand compared to stores without as some of the additional gas is consumed in generating electricity. The extent of this effect on gas demand is a function of the size of the CHP plant. To account for this the *Electrical Rating*, i.e. an indicator of CHP size, was included in the analysis of stores with CHP. The electricity produced by the plants is metered and combined with the electricity consumed from the grid for the purposes of this study; therefore the presence of a CHP plant does not affect the total electricity demand of the store.

B.3.1.2 Operational

Opening hours can be expected to have a direct impact on aggregated energy demand as when a store is closed the end-use energy demands for heating, cooling, lighting (internal and external), sales systems, restaurants, etc., are reduced; recorded hours of occupancy were also used by [23]. As the stores in the sample vary between conventional opening hours and being open 24 hours *opening hours* was included as a factor.

During day-to-day operation of a store the number of customers can affect various end-use energy demands. Heating and cooling is affected by heat gains from customers within conditioned spaces whilst heat losses can be affected by the opening of entrance doors as customers enter and leave a store. The end-use demand in customer restaurant's kitchens is also be affected by the number of meals prepared. In a similar way, the load on refrigerated cases is affected by heat gains when customers open and close doors on frozen food cases and when frozen and chilled cases are restocked. Whilst some of these effects may be minimal and difficult to identify in the signal of variations in end-use energy demands, the proxy indicator of *Volume of Sales* was selected to represent the scale of customers moving in, through and out of each store.

As discussed in section B.2, outdoor temperatures can influence refrigeration and HVAC loads, depending on the systems in place. For that reason, stores were divided according to their geographical location, adopted from [24], and Cooling Degree Days (*CDD*) and Heating Degree Days (*HDD*) were computed for each region with a base temperature (T_{base}) of 15.5[°C], using the online tool developed by BizEE Software [25]. The expectation is that as CDD increases, stores use more electricity for cooling, and as HDD increases, stores use more gas (or electricity) for heating. Nevertheless, internal air temperature was not included as a factor, because as mentioned in section B.2.2.1 most of the stores are remotely controlled and are expected to have the same internal air temperature at any given time.

Easting was selected as the difference in longitude between the westernmost part of the UK and the position of the store, while *Northing*, is the difference in latitude between the southernmost part of the UK and the position of the store. Both were included in the set of independent variables to represent the location of the stores.

All variables, unless otherwise stated, were sourced from readily available sources, e.g. the organisation's centralised databases. *Electricity Consumption* was measured at the Meter Point Administration Number (MPAN) using wireless loggers. Data was collected weekly for each hypermarket and summed over a period of 365 days to generate annual consumption data. Where a CHP plant was present, electricity generated from the plant was metered separately and added to the MPAN value. Total annual *Gas Consumption* for each store was provided by the supplier and verified from the in-store gas meter by an independent consultant.

Table B.2: Dependent and Independent variables

Dependent		**Type**
	Electricity Consumption [kWh]	Continuous
	Gas Consumption [kWh]	Continuous
	Gas Intensity [kWh/m^2]	Continuous
Independent		
Physical	SFA [m^2]	Continuous
	Total floor area [m^2]	Continuous
	Year built	Continuous
	Pre-Post 2002 (pre=1, post =0)	Dichotomous
	Ceiling Height [m]	Continuous
	No of Trading Floors	Dichotomous
	Food: Non-Food Ratio	Continuous
	CHP (yes=1, no=0)	Dichotomous
	Electrical Rating (of CHP plant)	Continuous
Operational	Opening hours (24hr = 1, not 24hr = 0)	Dichotomous
	Volume of Sales [£]	Continuous
	Sales/SFA [/m^2]	Continuous
Regional	CDD	Continuous
	HDD	Continuous
	Easting	Continuous
	Northing	Continuous

B.3.2 Analysis methods

Measurements of all variables were compiled for each hypermarket store, (N=215). The study dataset was then checked and adjusted for quality and outliers. From the initial sample, stores with missing values were removed (N=12), similar to stores that had undergone any type of development works (extension or remodelling) within the period investigated (N=9). With the remaining dataset standardised procedures were used to detect outliers where any data values more than 3 standard deviations from the mean were individually investigated. Whilst most of the data points falling outside of this range were found to be valid measurements and could be explained a number could not and were removed (N=6). This procedure ensured that stores that had experienced technical faults or structural changes in end-use energy systems or measurement systems were removed from the study sample dataset. This resulted in a complete study sample for electricity of N_{elec} =188 and a study sample for gas of N_{gas}=123, as complete gas consumption data was not available for a further 65 stores.

All variables were tested for normality and linearity and it was confirmed that all dependent and independent variables fulfilled the requirements of parametric tests, except *Gas Consumption*. *Gas Consumption* was found to have a bimodal distribution, which when investigated revealed significant differences between stores with CHP plants and those without. Separate analysis was therefore carried out for stores grouped according to the presence or absence of a CHP plant.

Statistical tests were applied to groups of dependent and independent variables to identify correlation significance of store characteristics and drivers of demand and goodness of fit of resultant regression equations. The dependent variables investigated were *Electricity Consumption* and *Gas Consumption*. Stepwise linear regression was used to identify significance of proposed independent variables which were selected on the basis of engineering understanding of electricity demands along with factors identified in other studies as discussed in Section B.3. These tests informed the design of multiple linear regression tests where analysis of the dependent variables resulted in three parallel equations; the independent variables included in each equation varied in relation to the dependent variables being investigated.

Stepwise linear regression, along with regression diagnostics, was conducted using SPSS [26]. This automated procedure resulted in automatic exclusion of independent variables that were computed to be statistically insignificant. Regression diagnostics were used to scrutinise resultant regression statistics for linearity, normality and homogeneity.

B.4 Results and discussion

Stepwise multiple linear regression was conducted using the full model of all variables listed in Table B.3.1.2. Through this procedure those variables that did not have statistical significance were removed from the regression models. The selected variables were then introduced into a standard regression analysis. Whilst this procedure removes variables that have weak signals in the dataset it is possible that influential factors are not accounted for, because they were found to be statistically insignificant in the regression models. This could be because the type of variables available in the dataset does not suitably represent them. This issue was considered when interpreting the results that follow.

B.4.1 Total annual electricity demand

Total annual electricity demand was found to be a function of physical size, volume of sales, composition of sales areas and factors related to year of construction. The resultant regression model, Equation B.1 shows 44.6% of the variability in *Electricity Consumption* is accounted for by the *SFA* of a store, and an additional 26.3% is accounted for by the *Volume of Sales* of a store. The addition of the *Food: Non-Food Ratio* increased this by 3.7%, while the addition of the *Pre-Post 2002* factor increased it by 1.2%.

$$\begin{aligned} ElectricityDemand[kWh] = 6.1x10^5 + 3.1x10^2(SFA[m^2])+ \\ 1.4x10^{-2}(VolumeofSales[£]) + 3.5x10^5(Food : Non - FoodRatio) \\ -2.1x10^5(Pre - Post2002) \end{aligned} \tag{B.1}$$

This model accounts for 75% (R^2_{adj}) of the variance in Electricity and is significant ($F_{(4,183)}$ = 146.251, $p < 0.001$). *SFA* and *Volume of Sales* have the greatest effect on the *Electricity Consumption*, with standardised β weights of 0.636 and 0.352 respectively (p<0.001), table B.3, while the *Food: Non-Food Ratio* has a smaller but still significant effect of 0.278. Pre-post 2002 has a significant but negative effect of -0.132, which means that stores built after 2000 consume less electricity than stores built before 2000. The effects of all the included independent variables are significant at the 0.001 level.

Table B.3: Beta weights of annual electricity demand

	B	Standard error *B*	Beta
(Constant)	612779.460	212430.406	
SFA [m^2]	310.980	31.452	0.636
Volume of sales [£]	0.014	0.002	0.352
Food: Non-Food Ratio	350913.729	67823.166	0.278
Pre- post 2002	-207067.485	68684.075	-0.132

This model is considered to be moderate to good as few variables prove to be statistically significant and half of the variables have comparatively large regression coefficients, i.e. of the scale of 10^5 kWh/yr for one unit variance. The model also shows that factors related to the composition of product lines, i.e. Food: Non-food Ratio, and the thermo-physical properties of construction, i.e. Pre-post 2002, do have a statistically significant influence on total annual electricity demand. This is as expected but as Year of Construction proved not to be significant the indication is that overall influence of construction properties is less than that of other factors.

Although the influence of SFA is as expected, i.e. the larger the store the more electricity it consumes, the strength of influence of this is less than expected. This is considered to be due to the impact of store volume, usage intensity and composition of product lines not being linear functions of SFA. In terms of electricity demand, where the size of cooling coils, the amount of cooling needed and the size of fans can be expected to have direct influence on HVAC electricity demand; increasing the volume of air to be conditioned in a store would result in increasing the total electricity demand. In other words, if stores had a linear relationship between SFA and store volume the relationship between SFA and electricity demand would be stronger. Similarly, composition of product lines, represented by the Food: Non-food Ratio, can affect the relationship between SFA and electricity demand. This is because whilst Food: Non-food Ratio indirectly reflects the relative extent of store floor area dedicated to refrigerated products, such that increasing proportions of floor areas dedicated to food products can be expected to result in increasing refrigeration demand, this ratio is independent of SFA. Usage intensity or footfall, as indirectly represented by Volume of Sales, can be expected to directly impact a number of electricity end-uses such as refrigeration, HVAC and cooking in restaurants. As this is not a linear function of store size (SFA), being more directly related to usage intensity, it also affects the relationship between SFA and total annual Electricity Demand.

A similar situation was found with usage intensity, as represented by Volume of Sales, where the relationship between usage and electricity demand was found to be statistically significant but not as strong as expected. This is likely because electricity end-uses that are directly affected by usage, in terms of the number of people using a store (i.e. HVAC, specialist services and other, for more specific end-uses within these categories see Section B.2.1), are relatively small components of total electricity demand and, in the case of refrigeration being the largest end-use, usage has a smaller direct impact.

Local climatic conditions would be expected to have a direct influence on HVAC cooling loads however the variables used to represent this, i.e. HDD, CDD, were found to have no statistical significance. This is considered to be partly due to HVAC being one of the smallest components of annualised total electricity demand, see Figure B.2, and that CDD and HDD are not normally distributed across the study sample. With HVAC being such a small component of aggregated annual electricity demand yet being the end-use demand most directly associated with outdoor temperature the statistical signal can be expected to be weaker than other end-use causal influences. It is be expected that the correlation exists but it is simply too small to emerge explicitly at the aggregated annual level. As an example this is a common finding when relating aggregated annual data with small scale but theoretically important factors.

Overall the multiple linear regression analysis of total annual electricity demand indicates that at the aggregated annual level, electricity demand can be reasonably well estimated by some but not all of the factors that would be expected on the basis of building energy demand theories. For example, HVAC, an end-use directly affected by the thermal performance of a building's envelope, has a statistically insignificant impact on total electricity demand compared to the main electrical end-uses of refrigeration, lighting and specialist services.

B.4.2 Total annual gas demand

Preliminary investigation of total annual gas demand revealed two significant sub-populations of stores without CHP (N=89) and those with a CHP (N=34). This would be expected to be influential as all the CHP systems are gas driven. The sample was divided into those without and with CHP before stepwise multiple linear regression was conducted. It was also found that annual total gas demand was not normally distributed within both sub-populations and that log transformation did not resolve this. Therefore gas demand intensity representing *Gas Consumption*, see Equation B.2 below, was adopted as the dependent variable. The use of gas demand intensity enabled us to determine *Gas Consumption* more efficiently by taking into consideration the store size.

$$GasIntensity[kWh/m^2] = \frac{Gasdemand[kWh]}{SFA[m^2]} \tag{B.2}$$

B.4.2.1 Annual gas intensity in stores without a CHP plant.

In stores without a CHP, gas is used primarily for warm air heating. Heating demand in these systems is a direct function of the volume of air that is heated and, to a lesser degree because of air recirculation, the outdoor climate conditions.

Through stepwise regression analysis, annual gas intensity was found to be significantly influenced by factors reflecting store size, volume and the composition of product lines. From the resultant model, Equation B.3, 29.5% of the variability in *Gas Intensity* is accounted for by the *SFA* of the store and an additional 12.9% is accounted for by the *Ceiling Height* of the store. The addition of the *number of trading floors* of the store increased this by 3.5%, while the addition of the *Food: Non-Food Ratio* of the store increased it by 0.7%.

$$\begin{aligned} GasIntensity_{StoreswithoutCHP}[kWh/m^2] = 3.8x10^2 - 2.0x10^{-2}(SFA[m^2])+ \\ 5.8x10^1(Food : Non - FoodRatio) - 1.7x10^1(CeilingHeight[m]) \\ -3.7x10^1(NooftradingFloors) \end{aligned} \tag{B.3}$$

The model is considered moderate and accounts for 50% (R^2_{adj}) of the variance in *Gas Intensity* ($F_{(4,84)}$ = 23.65, p <0.001). *SFA* and *Food: Non-Food Ratio* have the greatest effect on *Gas intensity*, with standardised β coefficients of -0.373 and 0.325 respectively (p<0.001), while the *ceiling height* has a smaller but still significant (p<0.01) effect of -0.283. *No of Trading floors* has a less significant effect of -0.156 (p=0.05). Whilst all the statistically significant variables have relatively small regression coefficients their B weights indicate relatively strong influence on Annual Gas Intensity, see Table B.4.

It would be expected that SFA would not be so influential on gas demand intensity as this already accounts for SFA. However, the above results show that increasing store size results in a small but statistically significant reduction in gas intensity, i.e. -0.02 kWh/m^2.yr.

Similar to electricity demand, climatic conditions, in this case represented by HDD, were not found to be significant. This is particularly interesting as the predominant use of gas is for warm air heating. It is considered that this indicates that the high proportion of recirculation of air in stores makes good use of internal heat gains and that fabric heat loss is minimal.

Whilst the resultant regression model is only moderate it does show that accounting for the range of product types, i.e. food and non-food, is of a similar order of importance as size and volume when predicting annual gas demand intensity. The results show that as the amount

Table B.4: Beta weights of annual gas demand intensity (stores without a CHP)

	B	Standard Error B	Beta
(Constant)	408.472	64.697	
SFA [m^2]	-0.023	0.006	-0.373
Food: Non-Food Ratio	44.311	12.508	0.325
Ceiling Height [m]	-18.547	5.294	-0.283
No of Trading Floors	-26.797	13.671	-0.156

of sales floor area dedicated to food products, relative to non-food products, increases the gas demand intensity increases. This is considered to partly reflect that some food products are presented in cooled cabinets and that some non-food products can have small heat gains, such as electrical products where TV walls, etc. are in use. Further investigation of the influence of more specific product types, e.g. electrical; clothing; ambient food; etc., could result in better prediction of annual gas intensity

B.4.2.2 Annual gas intensity in stores with a CHP plant.

In stores with a CHP gas is consumed for heating and to generate electricity. In these stores gas demand is therefore not only driven by the heating demand but also by the amount of electricity that is to be generated. Efficient use of CHP dictates that the use of the system needs to be driven by the demand for heat such that electricity generated is effectively a by-product of generating heat to meet in-store demands. In the context of such efficient CHP management gas demand in stores with CHP could be expected to have similar relationships with factors that affect heat demand as in stores without CHP albeit at a different scale due to comparatively lower efficiency in generating heat in CHP compared to high efficiency boilers.

Stepwise regression revealed that gas consumption in these stores is a function of size, the electrical capacity or rating of the CHP system, as well as the location of the store and the composition of product lines. From the resultant regression model, Equation B.4 below, 55.3% of the variability in *Gas Intensity* is accounted for by the *SFA* of the building and an additional 16.6% is accounted for by the *Electrical Rating* of the CHP plant. The addition of the *Easting* variable increased this by 4.0%, while the addition of the *Food: Non-Food Ratio* increased it by 3.8%.

$$\begin{aligned} GasIntensity_{StoreswithCHP}[kWh/m^2] = 7.8x10^2 - 4.9x10^{-2}(SFA[m^2]) + \\ 1.2x10^0(ElectricalRating[kWe]) - 4.3x10^{-2}(Easting[m]) \\ +9.0x10^1(Food: Non-FoodRatio) \end{aligned} \tag{B.4}$$

This model is considered good and accounts for 77% (R^2_{adj}) of the variance in *Gas Intensity* and is statistically significant ($F_{(4,29)}$ = 25.32, p <0.001). *SFA* has the greatest effect on *Gas Intensity*, with standardised β coefficient of -0.498 while the *Electrical Rating* of the CHP plant

Table B.5: Beta weights of annual Gas intensity (stores with CHP)

	B	Standard Error B	Beta
(Constant)	777.349	135.811	
SFA [m2]	-0.049	0.012	-0.498
Electrical Rating	1.192	0.310	0.344
Food: Non-Food Ratio	90.172	37.954	0.298
Easting	-0.043	0.015	-0.264

has a smaller but still significant effect of 0.344 ($p<0.001$). The location of the store (*Easting*) has a smaller effect of -0.264 ($p<0.01$). *Food: Non-Food Ratio* has a less significant effect of 0.298 ($p<0.05$), see Table B.4.2.2.

An interesting result is that the Electrical Rating of CHP systems has a significant influence on gas intensity. In these stores increasing size of CHP systems result in small, i.e. R^2_{adj}=1.2 kWh/m^2.yr, but statistically important, i.e. Beta weight=0.344, increases in gas intensity. Considering that CHP is most efficiently operated as a function of heat demand this finding suggests a degree of inefficiency in the use of these systems during the measured period. This illustrates that the regression method could be useful in identifying inefficient use or system faults.

The finding that location, as represented by Easting, is statistically significant is considered to be a reflection of the sample being small, N=34, and having large number of those stores in the southern part of the UK, see Figure B.3.

B.4.3 Validation

In order to validate these results, measured energy consumption of the following year was compared to that predicted by the models. These results are presented in figures B.4, B.5 and B.6. The validation of the electricity model shows an R^2 value of 0.76 that agrees with the original 0.75 value. This shows that the electricity consumption of hypermarkets is generally well understood and managed. The validation of the gas models shows lower R^2 values compared with the original models with values of 0.50 for gas intensity in stores without CHP and 0.77 for gas intensity in stores without CHP. Some of the outlier stores were investigated further in order to explain this result. The value for the model of gas intensity in stores without CHP plants can be partially explained by the subsequent installation of a CHP plant in one of the stores, and the re-calibration of temperature sensors in a further two stores. The value for the model of gas intensity in stores with CHP plants can be partially attributed to a faulty CHP plant in one of the stores. The removal of the store from the calculation increases the R^2 value from 0.55 to 0.62. This is exactly how these models can be useful to the organisation; they can identify stores that are consuming higher/lower than the average for further investigation.

Figure B.3: Location of stores with CHP plants

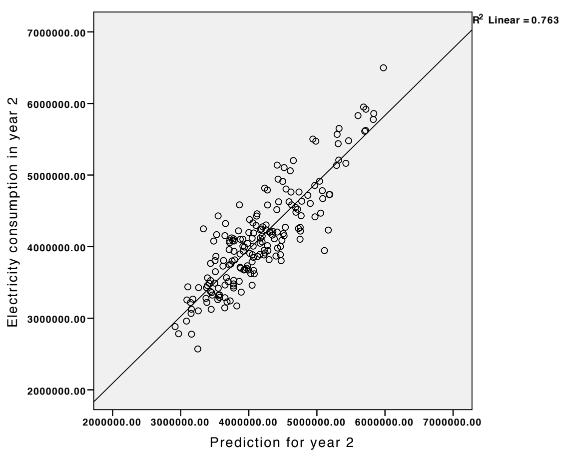

Figure B.4: Validation results for Equation B.1

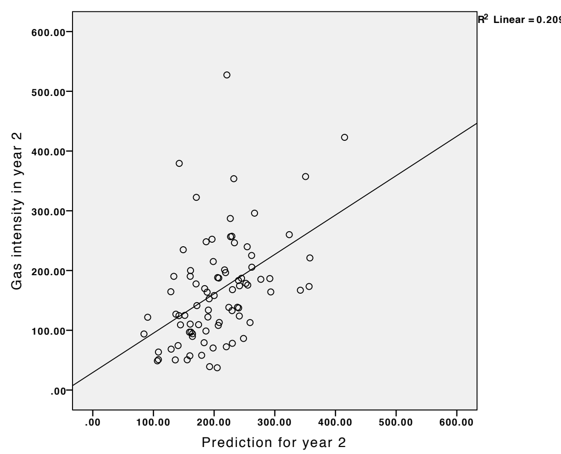

Figure B.5: Validation results for Equation B.3

B.4.4 Application of models

The models described in sections B.4.1 and B.4.2 enable quick identification of stores that have had significant changes in consumption that warrant further investigation, even though they cannot tell what actions are needed to achieve better performance. They can also be used to

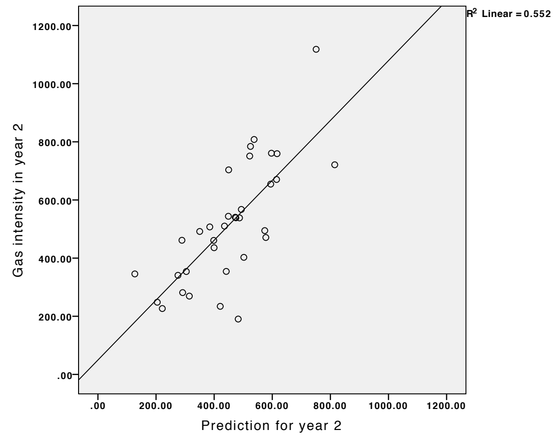

Figure B.6: Validation results for Equation B.4

identify the impact of efficiency measures. The electrical model accounts for aggregated operational factors explicitly, i.e. volume of sales representing the number of customers using a store, while the gas models account for operational factors implicitly. From an organisation's management point of view the starting point in ensuring efficient performance of their building stock is identifying how many and which stores have had significant changes in performance for no apparent reason, and then investigating these on a case-by-case basis. The models reported are considered to provide a reliable first order evaluation of the efficient operation of any hypermarket store within the organisation's stock.

B.5 Conclusions

Key drivers for energy demand in food retail stores have been identified through literature and examination of a sample of buildings. Following a statistical analysis, significant factors were determined and used to create multiple linear regression models for electricity and gas demands. Significant factors included the sales floor area of the store, the stock composition, and a factor representing the thermo-physical characteristics of the envelope. Two of the key findings are the statistical significance of operational usage factors, represented by volume of sales, on annual electricity demand and the absence of any statistically significant operational or weather related factors on annual gas demand. The results suggest that by knowing as little as four characteristics of a food retail store one can confidently calculate its annual energy demands. Using the models presented in this study, along with the actual consumption of stores, one can isolate stores that are not as efficient as expected and investigate them further to understand the reason for poor performance. At any year-end, stores with measured consumption significantly greater than that predicted by the models can be deemed to have scope for reduction in energy consumption. Even though the models cannot tell what actions are needed to achieve better performance they do enable quick identification of inefficient stores within the stock of hypermarkets. Whilst all the models are based on operational energy consumption, the electrical model accounts for aggregated operational factors explicitly, i.e. volume of sales representing the number of customers using a store, while gas models account for operational factors implicitly. From an organisation's management point of view the starting point in ensuring efficient performance of their building stock is identifying how many and which stores are performing inefficiently and then investigating these on a case-by-case basis. The relevance and value of this high level view is supported by the finding that many technical characteristics that would be expected to be influential, such as system performance; weather conditions and building fabric, are not as influential as usage and the primary physical characteristics of size and volume. The models reported are considered to provide a reliable first order evaluation of the efficient operation of any hypermarket store within the organisations stock. Limitations of this study are that the developed models cannot directly identify particular technical or operational factors that are causing inefficiency. However, whilst being based on data that varies in specificity of some causal factors it does provide empirical and explanatory approaches to assess not only the significance of inefficiencies but also what information and data is important in isolating these. These models can be improved by including more store types in the calculations, collecting energy data values for more than one year, and using more frequent data, such as monthly, weekly or half-hourly. In the future, these models can be developed further and used alongside TM46 [27], as a benchmarking methodology for food retail buildings.

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Appendix C: Paper 3

Reference:

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The Operational Efficiency of Commercial Food Refrigeration Systems: A Data Mining Approach

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Abstract

The energy demands of food retail buildings account for approximately 3% of the UK's energy consumption and resultant carbon emissions. Previous studies [1, 2] demonstrate that the greatest component of the electricity demand of food retail buildings is the cooling demand of the food refrigeration systems (ranging from 30 to 50%). Therefore a better understanding of the electricity demand for refrigeration would enable the development of effective energy management tools, including the evaluation of service and maintenance interventions to reduce operational electricity demand. Various methodologies have been developed and employed in the past for the quick identification of faults during the operation of commercial refrigeration systems. The focus of these methodologies has traditionally been on the temperature of food on the shop floor. The aim of this work is to enhance the existing fault-finding methodologies employed by a global multichannel retail organization, by enabling the identification of events that cause an increase in electricity demand of the refrigeration systems. This paper presents a methodology that analyses data from refrigeration systems and enables a more straightforward identification of faults. This includes data for electricity consumption, compressor run times, percentage of refrigerant in the receiver, temperature of air on and off the evaporator, discharge and suction pressures, etc. Control strategies and maintenance schedules as well as meteorological data for each site were also collected and analysed. Data mining methods were employed to remove known operational patterns (e.g. defrost cycles) and seasonal variations. Events that have had an effect on the electricity consumption of the system were highlighted and faults that have been identified by the existing methodology were filtered out. The resulting data set was then analysed further to understand the events that increase the electricity demand of the systems in order to create an automatic identification method.

C.1 Introduction

The energy demands of food retail buildings account for approximately 3% of the UK's energy consumption and resultant carbon emissions. Previous studies [1, 2] demonstrated that the greatest component of the electricity consumption of food retail buildings is the cooling demand of the food refrigeration systems (ranging from 30 to 50%). Therefore a better understanding of the electricity demand for refrigeration would enable reductions in the electricity consumption by identifying and implementing service and maintenance interventions. Currently there are a few modeling tools available that can be used to estimate the demand of commercial refrigeration systems, for example [3, 4, 5, 6, 7, 8]. However these do not readily take into account the operational behavior of the systems. Analysis of the operational behavior of the refrigeration systems can enable the development of more efficient management tools by incorporating intelligent operational monitoring and fault detection that leads to service and maintenance innervations.

There are many definitions of a fault available in the literature, for example see: [9, 10, 11]. In the retail environment, a fault in the refrigeration system is considered to be an incident that affects the temperature of the products in the display cases/cold rooms, or an incident that affects the shopping environment for the customers (e.g. water on the shop floor). The existing fault finding methodology of a retail organization focuses on these events. An alert is raised with the maintenance team when the products in the display cases/cold rooms have an estimated temperature higher than the threshold. The in-store technician of each store can also inform the maintenance team of any problems identified in situ (based on visual inspections e.g. water on the shop floor, dirt on the grilles; and/or aural inspections e.g. loud noise from the fans).

This study concentrates on the electricity demand of the refrigeration system. Therefore, for the purpose of this study, the authors consider the following definition of a fault:

- A **Fault** is an incident that has caused an increase in the electricity consumption of the refrigeration pack, which is unrelated to an increase in outside air temperature, and any periodic events (e.g. defrost cycles, stocking patterns).

As such, the aim of this work is to enhance the existing fault-finding methodologies employed by a global multichannel retail organization, by enabling the identification of incidents that cause an increase in electricity demand of the refrigeration systems.

The following sections present more information about the refrigeration systems used in this study, describe the available data, and propose a methodology for identifying faults. The proposed methodology is then applied to identify faults in a sample of ten stores, and two examples of uncovered faults are discussed.

C.2 The commercial refrigeration system

In order to understand the normal and faulty operation of refrigeration systems, the first step is to appreciate how the system operates. As shown in Figure C.1 the commercial refrigeration system referred to in this paper can be divided into two main parts:

1. The **Pack**, which is made up of the compressors and the condensers, and it is located away from the sales floor area, usually found on the roof of the building.

2. The **Cases**, which is a selection of cold rooms and shop floor display cases, with the evaporator element built into each one. The cases are divided into two main categories, the *Low Temperature*(-18 to -22°C, -0.4 to -7.6°F) and the *High*(or Medium) Temperature (+3 to +5 °C, +37.4 to +41°F).

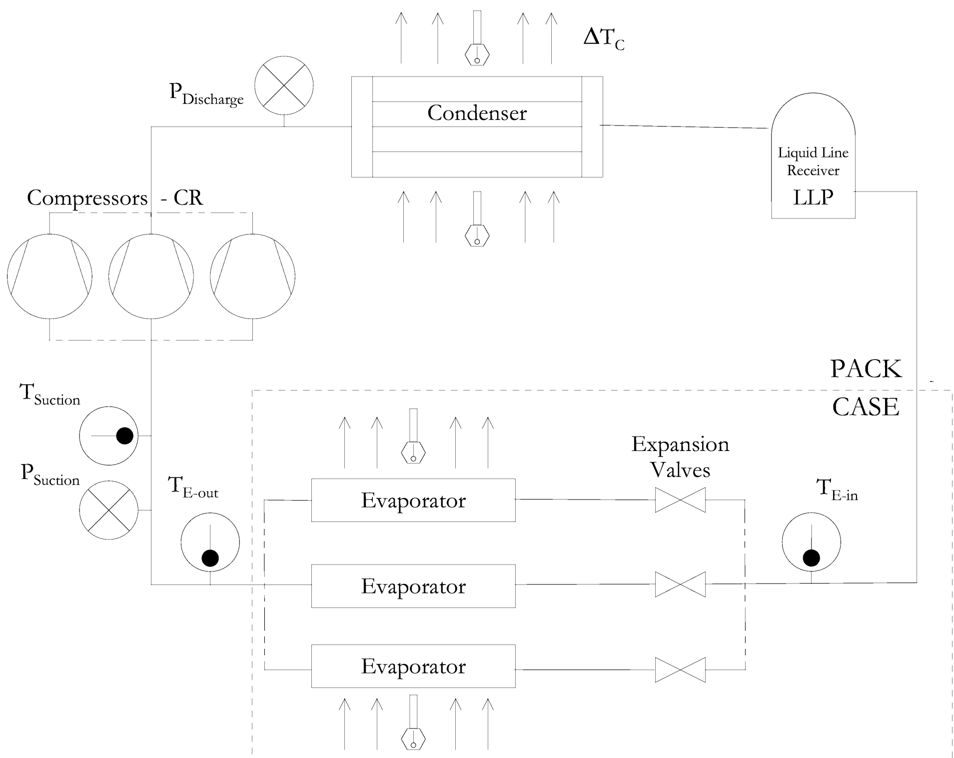

Figure C.1: Refrigeration system diagram demonstrating the pack and case sides, with available instrumentation (data collection points).

The load on the refrigeration system is known to be driven by conditions of the local thermal environment around both packs and cases. At the cases, heat is gained from the local environment through radiative, convective and conductive heat transfer [12, 13, 1]. The amount of heat gained is influenced by usage in terms of how often customers remove products, and the rate of restocking. During these actions there is ingress of warmer air circulating into the case thereby increasing the load on the refrigeration circuit. At the packs, the rate of heat taken out of the refrigerant circuit is a function of the temperature difference between the refrigerant entering the condenser ($T_{suction}$) and the local ambient air temperature ($T_{ambient}$), and the rate of airflow, driven by condenser fans, across the condenser heat exchanger. As the local ambient temperature increases the condensing temperature increases and in turn the condensing pressure increases. This causes a high-pressure difference across the compressors ($P_{suction}$ and $P_{discharge}$), which increases the load on the compressors and the condensers. This difference in pressure across the compressors has a large effect on the electricity consumption of the pack; it is therefore common practice to allow the suction pressure ($P_{suction}$) to float within limits, instead of setting it to an exact value, to use less energy. Overall the interdependence between each element of refrigeration systems means that a rise in external temperature affects the electrical load of the refrigeration system.

The electrical load of the packs incorporates the compressor rack and the condenser fan/heat exchanger. The remaining electrical load of the system would incorporate the load of the evaporator fans and defrost heaters (low temperature cases), as well as the load of lighting and circulation fans. In this study only the electrical load of the packs (E) will be analysed, as the recorded electrical load for cases includes other shop floor services, which are not of interest of this study.

C.3 Data and Analysis Methods

C.3.1 Data mining

This study approaches the subject of commercial refrigeration systems from the data point of view with the aim of gaining insights about the operational behaviour of the systems. Table C.3.1 gives a short description of the data available prior to this study, whereas the position of the instrumentation is indicated in Figure C.1. The assortment of representative stores was chosen for the investigation using the selection criteria below:

- Electricity data had to be available for each pack between 1 November 2012 and 1 November 2013.
- System operation data (such us suction pressure and evaporator temperatures) had to be available for the same time period to match the electricity data.
- Stores had to have been fitted with an 'Einstein E2' front panel controller; this controller provided the most comprehensive operational data out of all the installed controllers in the estate of the organization.
- Selected stores all use the same refrigerant, R404A, to keep the system configuration as similar as possible.

C.3.2 Methodology

Measurements of all variables shown in Table C.3.1 were compiled for each store. Subsequent analysis was carried out in IDL [15]. The dataset was checked for quality and completeness; where missing values were observed in the weather dataset ($<$10%), these were linearly interpolated. Standardized procedures were not used in this study to detect outliers; outliers were of interest and therefore needed to be retained. Electricity data was aggregated to hourly intervals to match the weather data frequency interval. It was expected that the electricity consumption of the refrigeration packs would be dependent on ambient temperature, see Ge and Tassou [3].

For this reason a regression model (see Tabachnick et. al. [16] for more information) was built for each pack based on the ambient temperature profile for that region. This regression model simulates the electricity consumption of the pack based only on weather, in the form:

$$Y = Const + W \tag{C.1}$$

Table C.1: Available Data

Symbol [Units]	Description	Frequency Interval
E [kWh]	Electricity readings from the distribution board servicing each pack	Half Hourly
$T_{ambient}$ [°C]	Ambient Temperature from the nearest available weather station to the store (UK Meteorological Office [14])	Hourly
MSI	Maintenance and Service Information data. Collected from the maintenance logbooks.	Time of addition
$T_{Suction}$ [°C]	Temperature of gas refrigerant before it reaches the compressor	Minutes
$P_{Suction}$ [bar]	Pressure of gas refrigerant before it reaches the compressor	Minutes
$P_{S\_setpoint}$ [bar]	Target pressure for the refrigerant before it reaches the compressor	Minutes
$P_{Discharge}$ [bar]	Pressure of refrigerant before it reaches the condensers	Minutes
CR	Indication of the compressor running or not	Minutes
LLP [%]	Percentage of liquid in the receiver (only available if the receiver was fitted with an ultrasound reader)	Minutes
Δ T_C [°C]	Temperature difference of refrigerant before and after the condenser	Minutes
T_{E_in} [°C]	Evaporator air in temperature, averaged across all cases	Minutes
T_{E_out} [°C]	Evaporator air out temperature, averaged across all cases	Minutes

where,

$$W = aT + bT^2 + cT^3 \tag{C.2}$$

Y is the predicted consumption for the pack in kWh, $Const$ [kWh] is the constant term in the equation (assumed to be consumption not affected by weather), W [kWh] is taken to be the effect of weather on the pack. $T_{ambient}$[°C] is ambient temperature as described in Table 1, while a, b and c are the coefficients for $T_{ambient}$ for each pack. In order to remove the effect of ambient temperature from the data set, W was subtracted from the actual consumption, E, of the store. Removing the effect of ambient temperature on the consumption of the system (W) makes the identification of faults easier as it removes the skewedness inflicted by an external factor. Based on what is known about the operation of the refrigeration packs, it was expected that the electricity demand would have some periodic patterns. For example, defrost cycles (scheduled to be carried out at specific time intervals depending on the type of case), time of day, and day of the week. For this reason the electricity data, after the effect of weather was removed, was transformed into the frequency domain using the Fast Fourier Transform (FFT) function in IDL ([17, 18]). The results showed that some frequencies have much higher amplitude than the rest, indicating that there are events that happen periodically with that frequency. For example an event with a period of eight hours could be representing the defrost cycles that happen three times a day; an event with a period of 24 hours could be representing the normal daily operation of a store, i.e. opening at 6am, stocking at 8am, high footfall around lunch time, stocking at 3pm, high footfall around 5pm, restocking at 9pm and store closing at midnight. Similarly a seven-day event would represent the weekly operation of the store, and the variations in opening hours between weekdays and weekends. The FFT has also highlighted that there are other periodic events in some stores that need further investigation (for example in Figure C.3.(c) there is a 12-hourly peak that could not be explained).

Following standard digital signal processing principles, the data set was cleaned by removing the peaks representing the periodic events caused by known factors. These were: the four/six/eight-hourly peaks depending on the defrost settings of the pack, the 24-hour peak, and the seven-day peak. It is worth noting at this point that the ‘zero’ or DC peak was not removed. The reason for not doing so was that the removal of this peak results in the exclusion of all noise from the original signal; the faults of interest to this study would fall under the ‘noise’ category as they are expected to appear randomly in the dataset. After the removal of the peaks, an inverse FFT was used to transform the data back into the time domain. For more information see Oppenheim et al. [18] and Stranneby and Walker [19].

As the focus of this study was to identify incidents that cause an increase in energy, any outlier data points needed to be investigated. In order to do so, the mean and standard deviation of each electricity data set was calculated, and any data points that fell outside two standard deviations from the mean were selected for further investigation. The aforementioned methodology is summarized in Figure C.2.

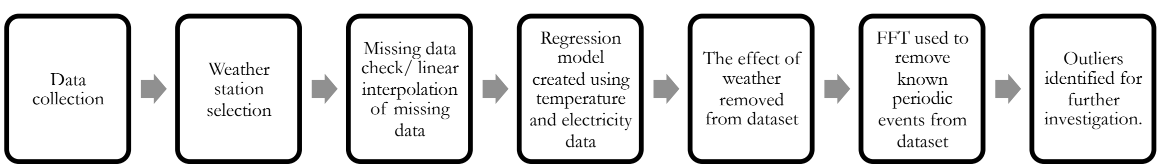

Figure C.2: Methodology for the identification of incidents that cause an increase in electricity consumption.

C.4 Results and Discussion

The methodology described above was used to analyse two data sets and identify faults for further investigation.

C.4.1 Example A: Low temperature pack - Missed opportunity

Figure presents the electricity consumption data of the pack and how it was transformed using the methodology presented in this paper. Figure C.3.(a) shows the original electricity consumption data. By looking at this figure one cannot be certain if there was a fault in the operation of this pack as there is only a small step change in the consumption towards the end of December. Figure C.3.(b) shows the regression model, equation C.3.2, for the same store. Figure C.3.(c) shows the FFT transform of the data, indicating the peaks that were removed, and the 12-hourly peak that cannot be explained with the available information. The final dataset and the outlier data selected for investigation are indicated in Figure C.3.(d).

The data for the outlier periods of time was closely investigated, and it was found that the compressor run times, CR, of the pack were much higher during those periods of time (Figure C.3.(e)). This was expected, as the more time the compressors are run, the more electricity they consume. However there were no obvious reasons for the extra compressor need. By looking at the suction pressure floating set point ($P_{S\_setpoint}$), Figure C.3.(f), this becomes clearer. $P_{S\_setpoint}$ was not floating as expected; it was set to the minimum value (0.81bar, 81kPa) for both of the high electricity consumption periods. This has caused the need for more compressors to be running at any given time to achieve the required suction pressure, leading to higher electricity consumption. Allowing the set-point to float in this example would have saved 20% of the pack's electricity consumption for that period of time (calculated from Figure C.3.(d)).

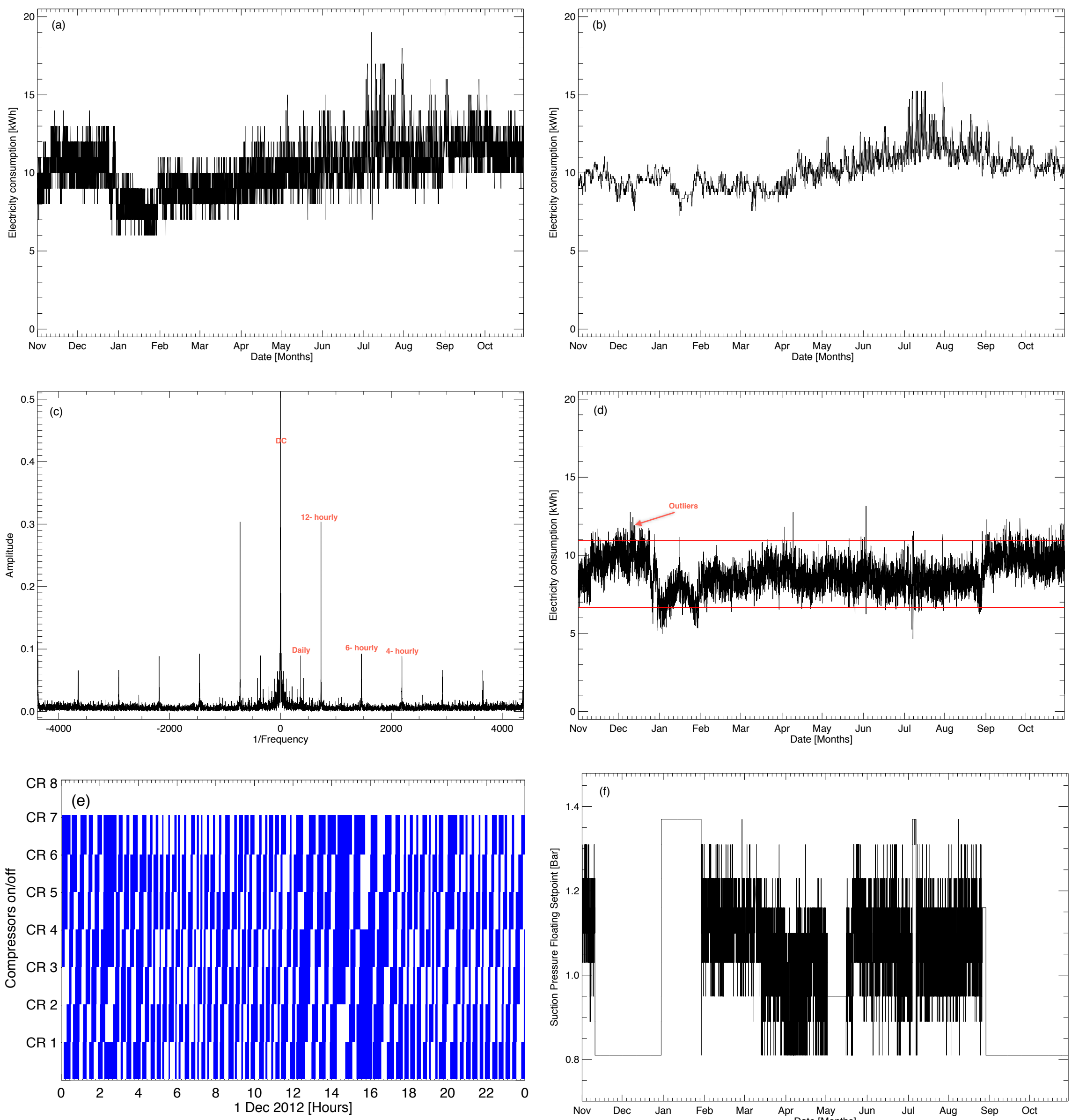

Figure C.3: (a) Electricity consumption of example A. (b) The modeled (Y) electricity consumption of example A. (c) FFT of the electricity consumption of example A. (d) The resulting data set, indicating outliers. (e) The compressor run times of the pack on Dec 1, 2012. (f) The suction pressure floating set point over the whole year.

C.4.2 Example B: Low temperature pack - Oversized system

Data for this store is presented in Figure . After applying the methodology to the original electricity data (Figure C.4.(a)), it became clear that there was a 15% reduction in the consumption occurring on February 5, 2013, Figure C.4.(b). This was caused by the installation of passive display doors that do not have anti-fog heaters installed. As seen in Figure C.4, the direct electricity consumption saving from this is not included in the data used in this work, as it would be affecting the case consumption. However there was an indirect effect of this installation, as the new passive display doors do not produce any heat, which reduced the overall cooling demand of the system.

The rest of the store data was fully investigated, and it was identified that after the installation of the new doors the suction pressure of the pack was floating around the minimum value of 0.81 bar (81 kPa), Figure C.4.(d). This could be considered normal, if the cases were at a higher temperature than the set-point, but there were no temperature alarms from the cases. Additionally the compressors in the pack were found to drop off too quickly, after ˜5 minutes of operation (Figure C.4.(c)). Both of these issues were unusual, and after discussions with the refrigeration engineers, it was concluded that both concerns could be caused by the following factors: (i) the installation of the passive doors caused the pack to be oversized for the number of cases connected to it, or (ii) a shortage of refrigerant in the system. As there were no records of temperature alarms from the cases, it can be assumed that there was enough refrigerant in the system; therefore this must be an oversizing problem. Fitting more cases to this pack, or switching one of the compressors to a variable speed would allow this pack to work more efficiently and use less energy.

C.5 Conclusion

This paper has presented a methodology that analyses the electricity consumption data from refrigeration systems and enables a more straightforward identification of faults. The examples included have demonstrated that this methodology can form part of a more advanced automatic fault-finding solution; potential faults were difficult to identify in the original electricity data set. However treating the data with the methodology described in this paper has made it simpler to identify potential faults, and look for probable causes. It was also shown that by monitoring the suction pressure of the packs, alongside the compressor run-times, one could identify further opportunities for electricity consumption reduction.

Future work will include the data analysis of more packs by implementing this methodology in an algorithmic form. The outcome of this work will inform the development of an automatic, real-time, fault-finding algorithm, able to quickly identify faults not already highlighted by the pre-existing methodology.

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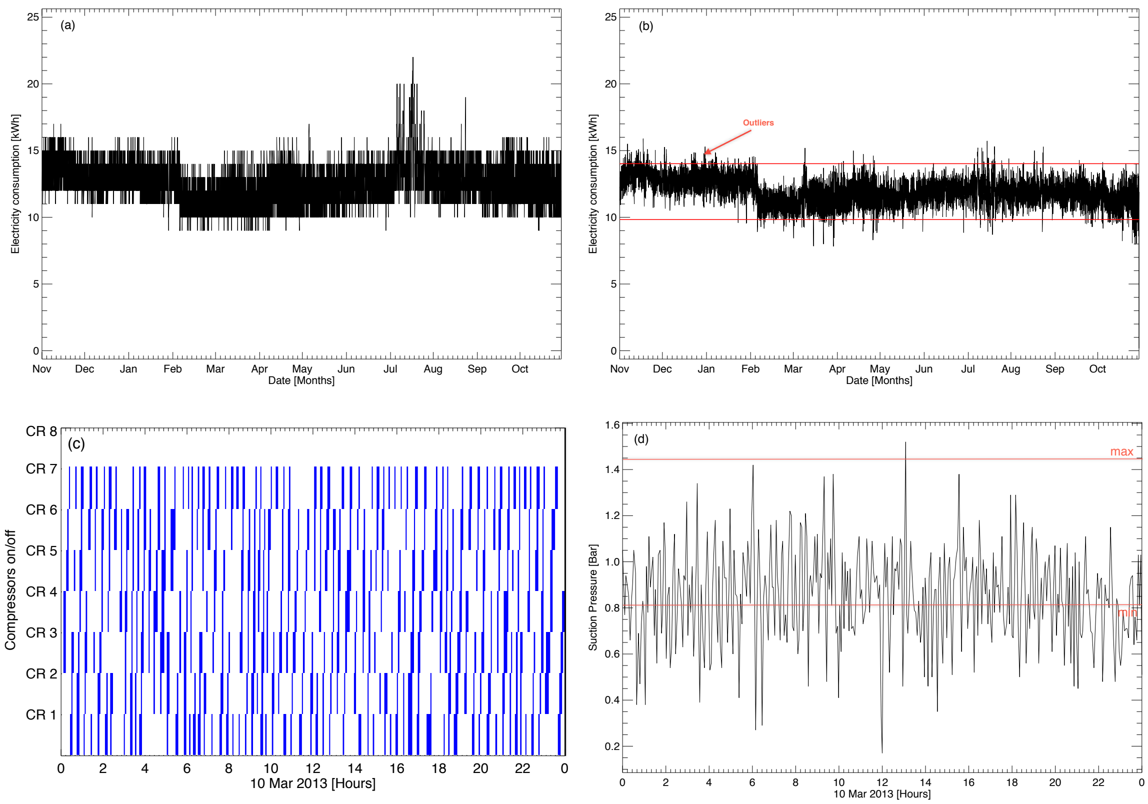

Figure C.4: (a) Electricity consumption of example B. (b) The resulting data set for example B, indicating outliers. (c) The compressor run times of the pack on March 10, 2013. (d) The suction pressure of the pack on March 10, 2013.

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