The analysis of primary metered half-hourly electricity and gas consumption in municipal buildings

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A thesis submitted in partial fulfillment of the requirements of De Montfort University for the degree of Doctor of Philosophy in Energy and Sustainable Development

This research programme was carried out in the
Institute of Energy and Sustainable Development, in collaboration with
Instituto Superior Técnico – Technical University of Lisbon

September 2009

Acknowledgements

This research work was conducted at the Institute of Energy and Sustainable Development, Leicester, UK, in collaboration with the Instituto de Engenharia Mecânica from the Instituto Superior Técnico – Technical University of Lisbon, Portugal.

I should like to express my gratitude to Professor Paul Fleming for giving me the opportunity to conduct this research, and for his close supervision and constant encouragement and support. I would also like to thank my second supervisor Dr. Greig Mill for his support in the statistical data analysis, and to my colleague Graeme Stuart for our long discussions on building energy management and data analysis. Also at IESD I should like to thank Dr. Neil Brown and Dr. Andy Wright for providing additional material and their viewpoints. I also should like to thank Dr. Peter Harris from Cheriton Technologies, Ltd for his enthusiasm and support at the early stages of the research.

This work was not possible without the data provided by Leicester Energy Agency, and for that I would like to thank particularly to Peter Webber, Prakash Patel and Jas for their patience and support over the review and discussions of data analysis results. I am most grateful to European energy managers who responded to the online questionnaire survey and expressed their opinions about the practical aspects of building energy metering and monitoring.

In Portugal, I should express my gratitude to Dr. Luis Alves and Professor Maria da Graça Carvalho for believing in me and providing the support to undertake this challenge. Also to my colleagues at IST for their constant encouragement, in particular to Rita Maia, Maria Cantista, Sandrina Pereira and Pedro Rosa. I would also like to thank Professor Joaquim Borges Gouveia for his friendship and advice.

Finally I should like to thank my parents, Ida and Juliano, and my brother Pedro, who were extremely encouraging over the entire process.

This work is dedicated to Sílvia, who inspired me and endured the ups and downs of academic research with patience.

I declare that the content of the submission represents solely my own work.

Vasco Guedes Ferreira, September 2009

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Nomenclature

Symbol	Definition
α_{D1}	Load factor on weekdays
α_{D2}	Modulation coefficient for baseloads calculated only for weekdays
α_{D3}	Load factor calculated for office hours on weekdays only
α_{D4}	Baseload modulation for office working hours on weekdays only
α_{D5}	Peak demand uniformity coefficient
α_{D6}	Baseload uniformity on weekdays
α_{D7}	Night impact on weekdays
α_{D8}	Night impact on weekends
α_{D9}	Lunch impact on weekdays
AHO	Area Housing Office
aM&T	automatic Monitoring and Targeting
AMM	Automatic Meter Management
AMR	Automatic Meter Reading
α_{W1}	Weekly load factor
α_{W2}	Weekly baseload modulation coefficient
α_{W3}	Weekend impact
b_1	Slope of the regression line
b_1	Linear dependency of energy with outside temperature below b_3
b_{1n}	Normalisation of b_{1n} using annual energy use
b_2	Linear dependency of energy with outside temperature above b_3
b_3	Change-point temperature
BEMS	Building Energy Management Systems
c	Non-weather related energy use or energy use at b_3
c_n	Normalisation of non-weather related gas use using annual energy use
CC®	Continuous Commissioning®
CO	Commercial and public office building type
CUSUM	Cumulative Sum of the Differences
DD	Degree-Days (Heating)
DEC	Display Energy Certificates
DR	Demand Response
E	Actual or modeled energy consumption
$\hat{E}$	Estimated monthly energy consumption
EPBD	Energy Performance in Buildings Directive
EPC	Energy Performance Certificates
EPH	Elderly People Home
ESD	End-use efficiency and Energy Services Directive
GIA	Gross Internal Area
HL1	Library and Museum building type
HL3	Sport centres with or without swimming pools building type
HVAC	Heating, Ventilation and Air Conditioning
IMT	Inverse Modelling Toolkit
NC	Neighbourhood Centres
NEEAC	National Energy Efficiency Action Plan
NPI	Normalised Performance Indicator
R^2	Squared correlation coefficient
RMSE	Root Mean Squared Error
SE	School building type
SQ10	Community centres building type
SQ21	Hostels and care homes building type
WAA	Warden Assisted Accommodation
z_i	Standard score or z-score

Abstract

This thesis addressed the need for improved analysis and interpretation of primary meter half-hourly energy consumption data. The current work offers a novel benchmarking technique that was tested for 6 types of municipal buildings. This approach is different from conventional annual benchmarking mainly because it uses electricity and gas data in half-hourly periods, together with outside temperature data.

A survey to European local authorities' metering and monitoring practices was conducted in order to assess municipal energy managers' current procedures and needs in terms of data analysis to assess building energy performance and to identify potential energy saving opportunities. The benchmarking approach was developed considering the energy managers' needs, but also the state-of the art in terms of building energy monitoring techniques, particularly building energy signatures, and the analysis techniques used on electricity grid demand forecasting.

The benchmarking approach is based on the use of a metric composed of several indicators that are related to the load demand shape profile and the building energy signature. The comparison of indicators for buildings of the same type using standard scores identifies uncommon load demand profile characteristics and/or gas dependency on outside temperature in specific buildings. The metric is able to support the identification of potential energy wastage, which is linked to the detection of opportunities to save energy.

The benchmarking technique was tested in 81 municipal building owned by Leicester City Council. This methodology can be applied to any non-domestic building equipped with primary meters for registering half-hourly electricity and gas consumption. In theory, this approach can also be applied to residential buildings, and to other short time series data types, for example quarter-hourly or 10 minutes interval data.

The main contribution of this thesis is to improve the objectivity of building primary meter half-hourly electricity and gas consumption data analysis and interpretation by using quantitative parameters, instead of subjective visualisation techniques. The interpretation of building consumption data in short time series periods can now be streamlined, automated and perhaps incorporated in existing energy analysis software. This thesis raises questions that can lead to future research projects aiming to improve the metric and also to enlarge the scope of its application to national and European scale, to other building types and to other utilities.

I have been impressed with the urgency of doing. Knowing is not enough; we must apply. Being willing is not enough; we must do.

Leonardo da Vinci

Chapter 1. Introduction to the research project

On the 2008 Climate Change Act the British Government has set a target of 80% cut in CO_2 emissions by 2050 and is aiming to show visible progress towards this target by 2020. In the Climate Action and Renewable Energy package, the EU has set a 20% CO_2 emission reduction target by 2020, which can be increased up to 30% if an international binding agreement on climate change emission reduction is reached under Post-Kyoto negotiations.

According to UNEP's report on Buildings and Climate Change: Status, Challenges and Opportunities (UNEP, 2007) 30% to 40% of worldwide energy consumption occurs in buildings, and this figure is increasing. Knowing that buildings can last over than one hundred years, the importance of decreasing energy demand of the existing building stock assumes major importance in the strategy to mitigate the impacts of climate change in the medium and long term.

In 2008, in the UK, buildings were responsible for about 65% of the CO_2 emissions, distributed by public sector, businesses and domestic users (DECC, 2009). The public sector is not the major contributor for total emissions from buildings, with only about 4% of total CO_2 emissions. However, the public sector has an important role because it can set best practice examples of CO_2 emission reduction practices for businesses, households, and other sectors of the economy. For instance, some local authorities in the UK are quite experienced in using automatic metering of electricity and gas. This would probably lead to the increasing interest in smart metering technology to improve building energy management. In fact, the UK government recently announced the intention of rolling out smart meters to all electricity and gas consumers to promote more efficient energy use. Consequently, the roll out of smart metering can take on the know-how that has been accumulated in municipalities and their equipment suppliers. The experience of municipal energy managers is of major importance in understanding how primary meter short-time series electricity and gas consumption data generated by smart meters can be used to identify and implement energy efficient measures.

The following sections present the aims and objectives of the current study, the methods used, the structure of the thesis and the policy context that drives the promotion of efficient energy use in buildings and smart metering technology.

1.1. Aims and objectives of the research project

The aim of this research project was to assess the usefulness of primary meter energy short time series data to identify energy saving opportunities in public buildings. Primary meter refers to the main meter that registers total consumption of a building, site or premise. Short time series data refers to hourly and sub-hourly energy consumption records from buildings; in the current work short time series data are half-hourly electricity and gas consumption data records. The research focused on a specific category of public buildings that are local authority buildings of different types: office and administrative, libraries, museums, leisure centres, community centres, schools and assisted accommodation for children and the elderly people.

This research project investigated the usefulness of analysing short time series data from primary energy meters to identify potential savings and improve building operation. The specific objectives of the research were:

- To study the current practices of European municipal energy managers, aiming to propose new tools to support building energy metering and monitoring using short time series data;
- To characterise quantitatively building energy performance using consumption profiles from half-hourly primary metered electricity and gas consumption data records;
- To investigate electricity and gas consumption profiles for different municipal building types using Leicester City Council database made available for the research;
- To develop and test a series of novel indicators to identify potential energy savings opportunities from undetected wastage through comparative benchmarking between buildings of the same type.

The subject of the research is relevant because there are important energy savings to be made in existing non-domestic buildings, resulting in significant reduction of carbon emissions. Typically, the identification of energy savings in buildings is carried out through surveys/audits. However these are one-off events, snapshots that just provide a static diagnosis of building performance, in a specific moment in time. Nevertheless, issues concerning the effectiveness of current energy auditing practice and the increasing availability of smart metering data is driving the development of continuous monitoring of building energy use. Therefore it is necessary to develop new methods and tools to conduct rapid and cost-effective building energy performance improvement and to support energy managers' activities. It would be beneficial if these tools focused on the use of primary meter short time series energy consumption data for automatically detect energy savings opportunities and provide energy efficiency advice to building managers and occupants.

This research shows originality in testing the usefulness of short time series primary energy meter data to identify specific energy saving opportunities in (non-domestic) municipal buildings. New empirical work was conducted that consisted of computing and analysing load demand profiles indicators and building energy signatures using electricity and gas short time series data from 81 Leicester City Council buildings. The result was the development of a novel benchmarking method for identifying uncommon load demand shape and building energy signature characteristics for the 6 types of municipal buildings studied.

1.2. General approach

The current research work builds on the author's MSc Dissertation completed in September 2002. The PhD research programme was started in January 2004. The work was conducted in part-time, and the author was based in Portugal. There was continuous supervision by Prof. Paul Fleming, regular meetings via Skype and frequent visits to Leicester for meeting with the supervisory team and colleagues at IESD and Leicester Energy Agency. During this time, the author integrated the team of several European projects on metering and monitoring energy consumption data in European municipalities and businesses. He presented several publications in conferences, workshops and summer studies. The main publications presented as main author are presented in appendix.

The author acquired an understanding of the real needs in terms of half-hourly data analysis and formulated a research question that supported a research programme for the development of an innovative tool, which not only help municipal energy managers, but can help users to reduce their building energy consumption. In other words, the author contributed to the development of a new energy management application for buildings and businesses that takes advantage of the short time series data generated by smart metering technology.

Generally speaking, smart metering refers to metering systems that are able to meter and register energy consumption (typically electricity) in short time series periods (hourly and sub-hourly). Smart meters also have one-way or two-way communication capabilities to send metered data for billing and monitoring purposes, and to receive information from the network operator and utility supplier. More information on smart metering is offered later in this thesis. In Europe, the most advanced country in smart metering installation is Italy, where about 86% of low voltage customers have already smart meters. Other European counties are mandating more frequent meter readings for billing purposes and indirectly supporting the installation of smart metering: this is the case of Sweden. Other countries are supporting pilot projects to study the technical and economic conditions for large-scale deployment of smart metering to all energy end-users.

This thesis uses real short time series electricity and gas consumption data acquired from an automatic metering system installed in municipal buildings to develop a new benchmarking approach for identifying potential energy saving opportunities. This thesis includes the application of different interdisciplinary skills. Different research methods were used, from online survey questionnaires to assess energy managers' needs in terms of energy metering and monitoring, to the application of advanced visualisation techniques and building inverse modelling methods for the analysis of half-hourly energy data. Indicators used in electricity demand forecast disciplines were studied and adapted to the analysis of individual building primary electricity and gas consumption half-hourly data. Descriptive statistics, but also more advanced statistical tests were also used to infer on results and to compare indicators per building type. Conventional benchmarking techniques using annual consumption data were also used, and results compared with the new benchmarking approach developed under this research. The new approach presented here, was validated using half-hourly electricity and gas consumption data available for a limited number of municipal buildings owned or operated by Leicester City Council, and equipped with an automatic meter reading system. The benchmarking approach proposed allows the quantification and comparison of electricity and gas load demand profiles and building energy signatures for different buildings, and the identification of uncommon profile characteristics that can be indicative of potential energy saving opportunities.

In 5 to 10 years it is expected that all buildings in Europe and USA and elsewhere, including residential, will be equipped with smart meters. There are still some issues in the definitions of in what consists a smart meter, but the fact is that in the near future all energy users, in particular the electricity users will be able to easily access to real time short time series energy consumption data. The Internet service providers and other ICT companies, such as Google are developing tools for acquiring and analysing this type of energy consumption data. Google PowerMeter initiative aims at receiving information from utility smart meters and energy management devices and provide users access to their home electricity consumption on their personal iGoogle homepage. This will generalise the access to energy information, in a first step only for electricity consumption data, but gas and other fuels, and water will probably follow.

This thesis contributes to the development of a framework for data management and data analysis techniques to help save energy in buildings, both domestic and non-domestic. The new benchmarking approach developed is able to take half-hourly electricity and gas demand profiles for different users, together with outside temperature data, and identify potential energy savings opportunities through the comparison of buildings of the same type. The methodology developed can be applied to large utilities' databases that hold energy consumption in short time series, and automatically produce tailor made advice for the different customers. Therefore it can be incorporated in a tool such as the Google PowerMeter and other software tools. The benchmarking technique developed in the current work can also be used to provide energy efficiency advice in more conventional formats, for instance in electricity and gas bills.

1.3. Thesis structure outline

The thesis is divided in eleven chapters. Chapter 1 presents the introduction and the thesis outline. Chapter 2 presents the review of published literature on the analysis of building energy consumption data. It presents the current situation of energy data collection, in particular the smart metering developments, and European projects on metering and monitoring. It also reviews the state of the art on the analysis techniques for metered short time series energy consumption data and diagnostics to improve building energy performance. The review presented justifies the meaningfulness of the research project, and its contribution to current knowledge on the analysis of short time series data to identify opportunities for optimising building energy performance. Chapter 3 presents a review of the visualisation tools for energy short time series consumption data.

Techniques such as 3D and 2D plots for visualisation of half-hourly data, line plots for aggregated data in monthly and weekly periods and load demand profiles are presented. The introduction of graphical indices for enhancing visual tools is also discussed with real data. These visualisation tools are used in subsequent chapters.

Since the focus of this research was on local authority buildings, an exploratory questionnaire survey of European municipal energy managers was conducted in order to get information on current practices, tools and techniques used. The main objective was to assess current best practice in the field and investigate the needs in terms of building energy data analysis as perceived by the practitioners. A summary of the survey results is presented in Chapter 4.

Chapter 5 describes the main technical specifications and operation of the Leicester's energy and water automatic metering system. The current study used raw data collected directly by the system, which had to be cleaned and prepared for the analysis using Matlab® software. This chapter includes a description of procedures applied to detect and correct data errors, re-sampling of missing data and selection of Leicester City Council buildings suitable for analysis.

Chapter 6 presents the analysis methodology implemented in Matlab®. The theory behind the computation of load demand profile shape indices is explained in detail, and the equations used for the calculation are presented. This chapter includes the presentation of the algorithm of the building energy signature model used to define the relationship between daily energy consumption and average daily outside temperature. The meaning of model coefficients is explained together with the statistical inference techniques to assess the goodness of fit and the model statistic significance.

Chapter 7 presents the results of the indicators calculation for electricity and gas consumption in all the buildings. It includes a detailed analysis of individual indicators and a critical appraisal of their importance to characterise building energy performance and to identify potential energy savings opportunities from undetected wastage. Less significant indicators are revealed and removed from further analysis.

Chapter 8 presents the breakdown of the relevant indicators by 6 building types. Post-hoc statistical tests were used to establish significant differences between electricity and gas consumption indicators for each building types. Chapter 8 establishes the basis for the comparative benchmarking analysis between buildings of same type, which is presented in chapter 9. In the latter chapter the use of standard scores is explained and the complete list of building energy consumption profile characteristics, with the identification of uncommon patterns of consumption is presented.

Chapter 10 discusses the research results in contrast with existing approaches to building energy performance assessment; in particular the normalised performance indicators and annual benchmarking. Future areas for further research are introduced.

Chapter 11 presents the conclusions that show that the research aims were achieved to the extent that it was possible to develop a metric that characterises building energy performance and identifies uncommon energy demand profile characteristics that may be linked to opportunities to save energy.

The next figure presents a schematic outline of thesis structure showing chapter content.

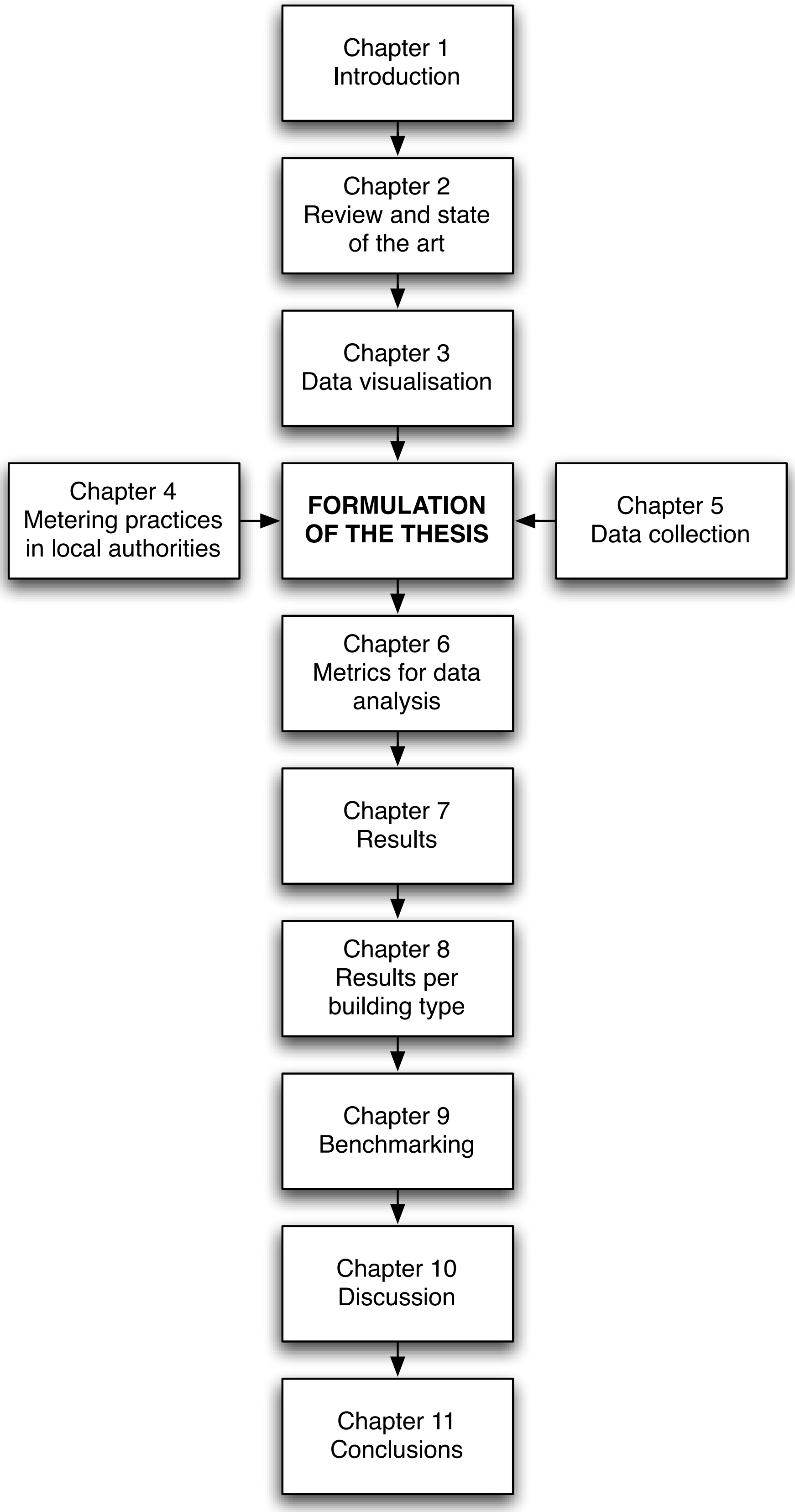


Figure 1. Thesis structure outline

1.4. EU building energy efficiency

EU Member States have recognised the importance of energy use in buildings to tackle the problem of climate change and Europe's dependency on imported energy products. According to a Green Paper, published in June 2005 under the title "Energy Efficiency - or Doing More With Less" (European Commission, 2005) the EU dependency on imports of fuels is about 50% of the EU's consumption, and dependency can reach up to 70% by 2030. The same publication refers that EU could reduce energy consumption by 20% by 2020. It continues and state that half of this potential could result from the application of existing legislation and programmes, particularly in the transport and building sectors, and the other 50% required new laws and more efficient behaviours from society, public and private institutions.

The Action Plan for Energy Efficiency (2007-12) adopted by the Commission supports the achievement of a 20% reduction of energy consumption by 2020. This Action Plan includes measures to improve the energy performance of products, buildings and services. It also includes measures to improve efficiency in the energy production and distribution and transport sectors. Support for financing and investments in energy efficiency, and the promotion of rational energy consumption behaviour are also included in EC's Action Plan.

Energy efficiency in buildings is one of the priorities of the Action Plan, mainly because buildings account for about 40% of EU energy needs. The Action Plan considers that large savings can be accomplished on residential and commercial buildings, with savings potentials estimated at 27% and 30%, respectively.

One of the main instruments for achieving this savings potential is the Directive 2002/91/EC of the European Parliament and of the Council of 16 December 2002 on the energy performance of buildings (EPBD), available on (European Parliament, 2002). EPBD aims at setting minimum energy performance standards in new and existing buildings, through the application of building energy certification and equipment inspection schemes. Member States are in charge of setting the minimum standards and ensure that qualified and independent personnel carry out that certification and inspection of buildings and equipments. For example, the implementation of this Directive in the UK was responsible for the development of building energy performance calculation methodologies and for implementation of Energy Performance Certificates (EPC) and

Display Energy Certificates (DEC). EPBD is already 7 years old, and has now entered in the process of revision to increase its impact on European building energy efficiency.

Buildings are at the core of the European Union's prosperity. They are important to achieve EU's energy savings targets and to combat climate change whilst contributing to energy security. An enormous unrealized savings potential lies dormant in buildings.

In Press release MEMO/08/693 on Recast of the Energy Performance of Buildings Directive, Brussels, 13 November 2008

Another powerful instrument for the promotion of energy efficiency in Europe is the Directive 2006/32/EC of the European Parliament and of the Council of 5 April 2006 on energy end-use efficiency and energy services and repealing Council Directive 93/76/EEC (European Parliament, 2006). The Energy Services Directive or ESD, as it is known, aims at establishing national indicative targets, incentives, institutional and financial support for the efficient use of energy, namely by creating the conditions for the development of energy services market and the delivery of energy-saving programmes. The ESD enforces the delivery of improved end-use energy efficiency to the supply, distribution and retail sale of energy (electricity, gas and other fuels). Under this Directive, Member States have to adopt and achieve an indicative target of 9% of energy consumption reduction by improved energy efficiency by 2016, to be delivered by a National Energy Efficiency Action Plan (NEEAC). Currently, all Member States have already submitted their NEEAC to the European Commission. Under these plans the public sector should be an example of the implementation of energy efficiency measures, and should inform the public and businesses on energy end-use efficiency best practice. Member States should promote energy services, energy efficiency programmes and financing mechanisms for energy efficiency. They should also support high-quality energy auditing and certification schemes to all final customers, equivalent to schemes implemented under the EPBD.

Additionally, the ESD suggests that Member States should ensure that all energy end-users have competitively priced individual metering and informative billing presenting their actual energy consumption. ESD suggests that energy bills are to be based on actual consumption, include comparison of present and past consumption and energy efficiency advice. For that, the Directive suggests the installation of individual meters when it is economically and technically viable. In what concerns metering, there are several countries, for example Italy, Sweden and more recently the UK, which have decided to roll-out the installation of smart metering for accurate and informative billing of electricity, and to prepare the provision of additional energy services and energy efficiency programmes.

In conclusion, energy efficiency is a priority in the EU policy agenda. The European Commission has set a target of 20% reduction of energy use by 2020 to be achieved by improved energy efficiency. The potential to improving building energy efficiency is large, particularly in non-domestic buildings, and this is a major priority of Member States. The two main drivers to support the energy efficiency in European buildings are the EPBD and ESD. Both directives suggest that public buildings should be an example in demonstrating and achieving the potential for energy savings. Additionally, there has been an increasing support for the introduction of technology to improve the understanding of how energy use, namely the introduction of more advanced metering systems to support better energy management and more efficient behaviours of Europeans citizens, businesses and institutions.

Chapter 2. Analysis of building energy consumption data

The aim of this research project was summarised as the assessment of building energy performance based on primary metered half-hourly electricity and gas consumption data. This chapter presents a critical review of published literature on short time series data collection and analysis for fault detection and diagnostics to improve building operation.

Usually, building energy performance assessments are carried out through energy audits or energy surveys. An energy audit is a systematic procedure that obtains adequate knowledge of the existing energy consumption profile of the building site, industrial operation, etc.; identifies and quantifies cost-effective energy savings opportunities; and reports the findings, as defined in EU Directive on end-use efficiency and energy services (European Parliament, 2006). From published literature on the effectiveness of energy audits, one concluded that energy audits are in fact essential for building (and industry) energy management (Ferreira, et al. 2006). However, the cost-effectiveness of reviewed energy auditing programmes is not conclusive. No clear indication was found on how cost-effective energy auditing programmes are. Nevertheless, evidence was found that short free energy audits can be a driver for improved energy efficiency.

The support of energy auditing activities by energy efficiency and energy auditing programmes has been a common practice in several EU countries. The EU Directives on energy performance in buildings (EPBD) (European Parliament, 2002) and end-use efficiency and energy services (ESD) (European Parliament, 2006) also supports building energy auditing. These European Directives have also been driving the introduction of metering and monitoring systems for improving energy management in buildings. For example, the UK building regulations that resulted from EPBD, demand the installation of automatic metering in all non-domestic buildings with useful floor area above 1000 m^2. The Portuguese building regulations require the installation of metering for all HVAC installations above 12 kW. Also in Portugal, the updated energy management regulations for industry requires that all installations that use more than 500 tonnes of oil equivalent per year have to install energy management systems.

2.1. Sources of metered energy consumption data

There are several ways to acquire time series energy consumption data. Generally, energy consumption data is derived from utility bills on a quarterly or monthly basis. This data is usually based on estimated readings and the billing period is variable. In order to get more accurate energy consumption data the alternative is to read manually the meters every month, week or day.

In the UK, since 1994, it has been mandatory that all the sites above 100 kW electricity peak demand to have half-hourly metering installed (Code 5, 6 and 7 metering and data loggers). These sites are billed according to a half-hourly electricity tariffs. The raw half-hour data can be made available to consumers when requested.

Also in the UK, and according to the Building Regulations – Part L2B 2006 (ODPM, 2006) for existing buildings others than dwellings, which came into force in April 2006, buildings with total useful floor area above 1000 m^2 are required to have Automatic Meter Reading (AMR) systems for energy utilities. These regulations also oblige that at least 90% of the estimated annual consumption of each fuel to the various end-uses (lighting, heating, cooling, etc.) should be metered, and that Technical Memorandum 39 (CIBSE, 2006a) is to be used for planning the sub-metering requirements. This Memorandum indicates that, for example, sub-metering should be installed in tenanted area in excess of 500 m^2, boiler installations greater than 50kW input power and chiller installations greater than 20kW input power.

The General Information Leaflet 65 (DETR, 2002) states that it is usually cost-effective to connect sub-meters to existing Building Energy Management Systems (BEMS). BEMS are computer-based systems which monitor and control building services to preserve indoor comfort and safety conditions, optimisation of energy consumption by end-use, equipment fault detection and diagnostics, and maintenance and facility management. A recent report from the Carbon Trust (Carbon Trust, 2007a) reinforces the idea of inter-connecting half-hourly meters with the BEMS system, to monitor consumption in order to manage and control buildings' energy use

It is expected that a significant number of buildings have been equipped with metering and sub-metering systems in recent years; and an important share of these systems will have AMR capabilities. AMR is a one-way system that collects data from meters via phone line, low power radio, GSM, Internet, etc, and stores it in a central computer or a server database. AMR can be applied to all building utilities: electricity, gas and water.

Usually AMR systems are used to collect data in short time series mainly for billing purposes. For example, in the UK the AMR data collection standard for electricity consumption is half-hourly period. However, this data collection frequency varies from country to country. Table 1 presents the primary electricity metering periods in some EU countries, which is normally used for utility billing.

Table 1. Metering periods in some EU countries, adapted from (Eurelectric, 2003)

Country	Metering period
Cyprus	20 minutes
Czech Republic	Hourly; in some cases 15 minutes
Denmark	Hourly
Finland	Hourly
France	10 minutes
Germany	15 minutes
Hungary	Variable; half-hourly for large costumers
Ireland	15 minutes
Netherlands	15 minutes
Norway	Hourly
Poland	Hourly
Portugal	15 minutes
Spain	Hourly
Sweden	Hourly
United Kingdom	Half-hourly

AMR systems allowed the introduction of automatic Monitoring and Targeting (aM&T). aM&T is a common abbreviation used to define a system that automatically collects and analyses energy consumption data and compares it to set targets. aM&T systems include meters (typically the utility primary meter is adapted to aM&T), automatic data collection, databases and analysis software with reporting capabilities. aM&T systems are used to monitor electricity, gas, water, fuel oil, steam, etc. wherever possible in short time series data. aM&T is a development of M&T, which as been promoted in the UK since the 1990's. M&T is based on the routine application of analysis techniques to readily available energy consumption time-series data to monitor energy consumption against set targets (DETR, 1998a, b), described on Energy Services and Technologies Association website and on several Carbon Trust publications.

2.1.1. Experiences of aM&T in European projects

This thesis has been developed in close collaboration with the consortium of two European demonstrations projects of automatic metering and monitoring technologies in municipal buildings: Intelligent Metering and ENERinTOWN projects.

The Intelligent Metering project - Energy Savings from Intelligent Metering and Behavioural Change project has involved 7 partners from 4 European countries. It was coordinated by Leicester City Council (Leicester Energy Agency) and project partners have been Energieagentur Waldviertel and Sonnenplatz Großschönau (Austria), County of South Jutland and Esbensen (Denmark), ENERGIE 2000 e.V. (Germany) and IT Power (UK). This project was co-funded by the Intelligent Energy Europe programme (Grant Agreement: EIE/04/107/SO7.38635). The overall objective of this project was to demonstrate that aM&T systems can be used to identify and support the implementation of energy savings from behavioural changes of municipal buildings occupants, (Webber, et al., 2007).

The Intelligent Metering project was responsible for the installation of aM&T systems in about 70 local and regional public sector buildings (including offices, leisure centres, community centres and kindergartens, schools, etc.). Different aM&T systems were used, but a common data format and database was set up to compile all the data collected. Data was displayed on the project Internet website: www.intelmeter.com. The project enabled building users to visualise half-hourly energy or water consumption data for their buildings in order to encourage changes in the behaviour and support the implementation of energy saving opportunities identified. Savings identified were from building occupants behaviour change, re-setting timers and heating controls and elimination of water leaks.

The ENERinTOWN project - Monitoring and control of energy consumption in municipal public buildings over the Internet, supported by Intelligent Energy Europe programme (Grant Agreement: EIE/05/118/SI2.419653), demonstrated the potential of Internet based metering and monitoring systems for identification of energy savings in European public buildings. This project started in January 2006 and ended in June 2008. Under ENERinTOWN project, aM&T systems were installed in 100 municipal buildings in 7 European countries: Spain, Portugal, Lithuania, Italy, Ireland, Greece, Germany and France. During the implementation of ENERinTOWN metering and monitoring systems, project partners experienced a mix of barriers and successes, (Ferreira, et al., 2008). The intended technical specification is described in Figure 2. The concept was the use of electricity meters, equipped with data logger for storing electricity data and gas pulses. Data stored in the electricity meter was sent through the Internet to a central database. However, there were technical difficulties on the integration of systems and communications (between meters, and between meters and databases). In some buildings it was not possible to access to Internet for security reasons. Alternative solutions for communication data from meters to database had to be sought. Project partners were free to select the most suitable aM&T system. In the end data acquisition from meters to the database was done using TCP/IP or landline, but the most popular communication solution selected by project partners was the GSM.

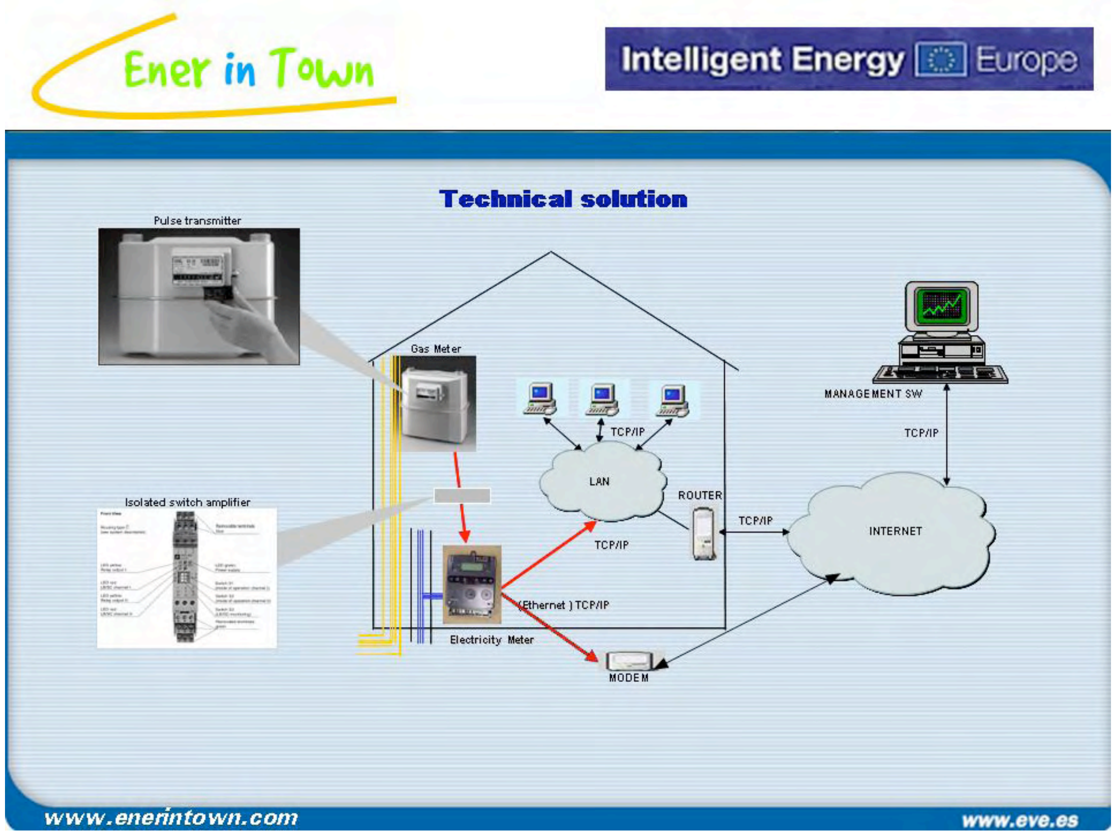


Figure 2. AMR technical specification intended for ENERinTOWN project

Savings identified by aM&T systems installed under ENERinTOWN project were mainly on switching-off lighting, heating and equipment when buildings were not occupied. Most partners trained municipal energy managers on the use of the proprietary software systems for data acquisition and analysis. However, most of the analysis was actually done using standard spreadsheet software that they were familiar with to complete the analysis e.g. MS EXCEL. More information on ENERinTOWN project can be found on the website: www.enerintown.com.

2.1.2. Future developments in metering technology

These European projects aimed to test different AMR and aM&T technologies and to investigate the market interest on these technologies. Liberalisation of energy markets, and the creation of the Internal Electricity market, implementation of Directive related to energy efficiency and the integration of energy and ICT technologies are important drivers for the development of AMR in Europe. However, there is no common harmonised technology for AMR or aM&T in Europe or elsewhere, and the maturity of AMR markets varies from country to country.

Additionally, technology is developing very fast, and new trends emerge quite rapidly. Smart metering is the generic term used to describe AMR and Automatic Meter Management (AMM). AMM can be described as intelligent metering services based on two-way data communication. It expands the scope of AMR from just providing meter readings to two-way real-time data communication between customers, suppliers and the distribution network operators. AMM allows the development of new services and additional benefits in the electricity supply chain, (Vasconcelos, 2008). The introduction of smart meters can be beneficial for electricity consumers, suppliers, and networks operators and to the general public. So far, smart metering has been applied mainly to AMR for electricity only. It is expected that smart metering will also be applied to gas, water and other utilities.

To energy users, smart metering enables more accurate meter readings, and billing, greater tariff variety and flexibility, facilitates procurement and supplier changes. Another important feature, under study in this thesis, is the ability that smart metering offers to manage and optimise consumption energy consumption. Another increasingly important area of research is the introduction of Demand Response (DR) and dynamic tariffs to increase the load management opportunities. DR is a set of strategies that can be used in competitive electricity markets to increase the participation of the demand-side, or end-use customers (IEA, 2003). In a market with DR mechanisms, customers are exposed to real-time prices and may respond by changing their load demand profile shape and by introducing energy efficiency measures or self-generation to reduce total or peak demand. Alternatively they may choose not to respond and consequently pay the market price for electricity. DR is only possible if AMR and AMM smart metering technologies are available.

The introduction of smart metering allows suppliers to differentiate services provided to customers and to have more information about their supply contracts portfolio. For example, suppliers can promote the diversification of pricing options, the provision of energy management services and demand responsive tariffs. The supplier change process can be streamlined with the introduction of smart metering, and consequently increase competitiveness. Additionally, suppliers can optimise their supply contracts portfolio, increase forecast capabilities and therefore enhance their negotiation power in the electricity market.

In conclusion, the increasing introduction of smart metering in electricity networks will empower customers to use their resources more efficiently. One of the major public advantages of smart metering is in fact the ability to introduce energy efficiency measures in all steps of the electricity supply chain. Nevertheless, smart meters will not save energy by themselves. Smart metering can be used to promote end-use efficiency by providing accurate information, raising awareness of consumers about their energy use and encourage them to become more energy efficient. DR mechanisms that are directly conducted by the customer can also provide the right incentives to behavioural changes and more efficient use of electricity.

Smart metering generates large amounts of short time series data that need to be used to generate useful information and knowledge. The focus of this thesis is on how this short time series energy consumption data can be used for building energy management. The next section offers a review of published literature on the analysis of primary meter short time series data, and also on the analysis of short time series data produced by sub-metering and BEMS systems.

An important reminder is that usually smart metering technology is considered for electricity only. However, there is no technological barrier for the application of smart metering technology to gas and other fuels, and also to other utilities such as water.

Most the techniques for the analysis of short time series energy consumption data presented in the following section are also generally applied to electricity only. Short time series gas consumption has only become available recently, and therefore very little has been done in the analysis of half-hourly gas consumption. In principle, there are no obstacles to the application of the same techniques used for electricity to the analysis of short time series gas consumption, as it is demonstrated further in this research.

2.2. Analysis of short time series energy consumption data

In the USA, 20 years ago Haberl and Vadja (1988) and Haberl and Komor (1990) suggested the use of daily and hourly electricity consumption data to improve energy audits, and to help diagnose problems in small commercial buildings. They found that metered data analysis provides useful information when presented to administrative and maintenance staff. These papers suggest a combined approach of analysis of available energy consumption analysis (monthly, daily, or sub-daily) and building manager feedback to identify energy saving opportunities. They stated that energy audits should be diagnostic in nature, and based on the analysis of metered data, rather than a rigid approach based on checklists. Haberl and Vadja (1988) concluded with the idea that energy efficiency requires continuously measurement of performance and savings in order to secure long-term results.

The use of metered data to improve building operation has developed since. Continuous Commissioning® (CC®) in the USA (Liu, et. al 1996) is defined as an ongoing process that uses measured hourly energy use and other operational short time series data (typically: outside and internal temperatures, hot water temperatures, chilled water temperatures and flow, humidity, etc) to improve building operation. They found that continuous commissioning often provided as much or more savings than energy efficiency retrofits, and suggested that CC® should be the first stage in any energy efficiency program. They found that about 80% of energy efficiency opportunities found by CC® are related to control systems, and therefore can be implemented in buildings with BEMS systems that include automatic controls. Potential savings identified from CC® were found to be related to resetting schedules, changes in ventilation rates, reduction in static duct pressures, use of variable speed drives and changes in specific control strategies.

Claridge, et al. (1999) suggested the use of Whole Building Diagnostics as methodology to conduct CC®. Whole-building diagnostics is a top-down approach to building diagnostics in which the data on whole building heating, cooling, air temperature and electricity consumption data, etc., is analysed in order to identify energy wastages and failures in building operation. They classified whole-building diagnostic procedures in two major categories:

1. Visual analysis of time series data, and,
2. Use of physical or empirical models of building energy consumption.

The first category uses the visual inspection of short time series data to diagnose building problems. The time series whole-building diagnostics requires separate data channels for heating, cooling, and other electrical uses. The typical results are the assessment of operational schedules, opportunities to turn equipment off and thermostat setting-up.

The second category uses time series energy data and building simulation to diagnose problems and optimise building operation. Because construction of a building simulation model is very time consuming, simplified models based on energy signatures can be used instead. These are typically inverse models, as presented in (ASHRAE, 2001), and explained in greater detail later in this thesis.

Claridge et al. (1999) concludes stating that whole-building diagnostics based on time series data and empirical models are helpful for identifying problems and probable cause for those problems; however, the confirmation of causes for energy wastage need to be confirmed by additional on-site measurements, site visits and informed dialogue with the building manager.

Conversely to whole-building diagnostics, component-level diagnostics can also be applied. This is a bottom-up approach, which focuses individual equipments and individual performance levels. The baseline for component-level diagnostics can be set using design calculations and equipment manufacturer's data. Diagnostics in HVAC systems are an example of component-level diagnostics. In fact, this has been an intensively researched theme over the last decade. The main references on this topic are (Lee, et al., 1996a, b, 1997; House, et al., 1999; Dexter & Pakanen, 2001; Wang & Xiao, 2004; Katipamula & Brambley, 2005).

A comprehensive comparative guide to (whole-building and component-level) diagnostic tools for large commercial air-conditioned building is offered in (Friedman & Piette, 2001). The latter offers a definition of manual and automatic diagnostic tools for building performance assessment. Manual diagnostics tools are said to require a knowledgeable analyst to identify faults and problems using plots and information automatically generated by the tool. In contrast, automated diagnostics reduce or eliminate the need for human reasoning in detection and diagnosis of problems by automating the process of analysing data. Brambley and Pratt (2000) described that automated diagnostic tools using a combination of models, statistical methods, and expert rules to detect operational problems. Haves (1999) suggests that the initial step in fault detection and diagnostics require is setting a baseline of performance using knowledge bases and quantitative models. This should be followed by a comparison of measured data with the qualitative (for example expert rules defined for system operation), or quantitative models (for example based on building simulation). The last step, i.e. the diagnostics of the fault requires the analysis of differences between actual and predicted performance and understanding the causes of those differences.

The International Energy Agency (IEA) has been working on building energy fault detection and diagnosis since the early 1990s. IEA work groups are composed by world leading experts in the field of building energy analysis and performance assessment. Initially, IEA focus on real time HVAC simulation, and Annex 25 work group produced important references on basic concepts and fault detection and diagnosis approaches

(Hyvikinen & Kairki, 1996; Hyvikinen, 1996). Following this, Annex 34 work group on computer aided evaluation of HVAC system performance, and in 2001 Annex 40 was set-up to validate and document tools for commissioning buildings to improve performance and save energy. Currently, IEA Annex 47 is taking further the legacy of previous work groups and focusing on enabling cost-effective commissioning of existing and future buildings in order to improve their operating performance. Results will be published at the end of 2009. IEA - Annex 40, the workgroup on commissioning of building HVAC systems for improved energy performance, developed an interesting methodology, called Operation Diagnosis. This is basically a methodology to manually inspect building systems and services operation using advanced visualisation techniques (Bauman, 2003, 2006) and (Visier, 2005). Multi-dimensional visualisation techniques are applied to records of operation data (energy consumption, temperatures, humidity, scheduling, etc.) usually stored in BEMS systems. Data is usually short time series, e.g. 2, 5, 10, 15 or 30 minutes interval data.

The objective of Operation Diagnosis is to use short time series data to gain an insight into the performance of building systems operation and detect existing faults. To avoid time-consuming analysis of large amounts of data, Operation Diagnosis uses a methodology based on normalisation of annual energy consumption and 2D visualisation techniques to get a quick overview of the data and to identify potential savings. Numerical analysis can also be applied to provide more detail on the quantification of potential savings, and measures to achieve the potential savings identified. Operation Diagnosis methodology can be described as a three-step approach:

- The first phase is on the assessment of energy performance through the calculation of total energy consumption, and producing normalised benchmarks (corrected for weather and floor area) with monthly and annual energy consumption and carbon emissions.
- The second phase in Operation Diagnosis is the evaluation of operation schedules against actual occupancy period of the building. Only with short time series data is possible to do this evaluation, and assess any existing differences between equipments operating hours and building occupancy periods. Bauman (2003) suggests that this can be made using carpet plots, very similar to the contour plots used by Ferreira, et al. (2003), and similar plots presented later in this thesis.
- The third phase Operation Diagnosis is on the evaluation of operation conditions. This is done by investigating interdependencies between recorded variables, such

as for example electricity consumption and outside temperature. Operation Diagnosis uses short time series data from BEMS and therefore it is possible to assess the interdependence of several variables, for instance: operation of valves, fans, and pumps, against chillers supply and return water temperature and outside temperature.

IEA Annex 40 workgroup concluded that Operation Diagnosis was very helpful in improving building energy performance, particularly in presenting information and discuss identified measures with building managers. They also found out that some measures identified by Operation Diagnosis need further on-site measurements and inspection to get more detailed information to assist decision and improve numerical saving quantification. The typical energy efficiency measures detected by Operation Diagnosis are:

- Correction of operation times regarding actual working schedules;
- Implementation of improved energy systems control strategies;
- Re-implementation of proper control strategies;
- Adjusting of existing control settings.

In conclusion, there are several diagnostic methodologies to improve building operations. These methodologies have different levels of data requirements. Typically, whole-building diagnostic and component-level diagnostic tools require BEMS data. This data is usually short time series for temperature, humidity, and electricity by end-use, cooling and heating energy, water and air flows, HVAC valve positions, etc. However, not all the buildings have this short time series data for end-uses, some have only short time series for the primary meters and others even only monthly or annual energy consumption data.

Friedman and Piette (2001) extended the classification of building diagnostics tools in three categories (annual benchmarking, energy monitoring, and operational diagnostics) in relation to the data inputs required. The following table presents the classification of building diagnostics tools according to available data inputs, and following sub-sections describe these in detail.

Table 2. Classification of building energy diagnostic tools for improved performance - adapted from (Friedman & Piette, 2001)

Level	Data	Result	Example
Annual benchmarking	Utility bills, floor area, location, degree-day correction factor.	Building metrics for comparison over time or against other buildings.	kWh/m^2 and kWh/m^3
Energy monitoring	Utility bills, primary metered data and sub-metering.	Understand patterns of energy use, major end-uses and utility rate analysis.	Breakdown energy use (%hot water use, % HVAC, etc.).
Operational diagnostics	BEMS/EMCS end-use short-time series data: temp., energy, air and water flow rates.	Detection of energy wastage from controls, equipment and system interactions.	Energy wastage from simultaneous heating and cooling.

2.2.1. Annual energy benchmarking

Annual benchmarking is a method for comparative assessment of building performance. Buildings energy benchmarking is normally conducted using total annual energy consumption, normalised by weather and floor area.

Normalisation is necessary to allow the comparison between buildings of different sizes, or located in different climatic regions. Normalisation is usually defined to be a common basis of differentiation between building size (for example floor area or total energy consumption), climate (outside temperature, humidity or amount of solar radiation) and operational factors (such as efficiency of systems, behaviour of occupants, etc.).

A typical benchmarking method used in the UK is the Normalised Performance Indicator (NPI). NPI for a non-domestic building is the ratio between the annual energy consumption and a determining factor, usually the building gross internal floor area – kWh/m^2, i.e. energy consumption is normalised by floor area. NPI can be calculated separately for electricity and other fuels. The annual energy consumption is normalised to take into account weather variation, building exposure and occupancy hours. Different drivers or determining factors can be used, depending on the building type. For instance, the number of pupils or building volume can be determining factors for assessing the energy performance of schools and hospitals, respectively.

The NPI of the building is then compared with the yardstick, representing the typical energy consumption for similar type buildings. The building can be classified as good, fair or poor according to its energy performance. This is similar to what is described in the guide (Carbon Trust, 2004) for benchmarking energy consumption of local authority buildings in the UK. This classification is a relative measure of how good or bad the building is performing. It can be said to be a unsophisticated method for evaluating building energy performance, because there may be exceptional reasons for explaining good or bad NPI that have nothing to do with efficiency. A common factor that affects NPI is the incorrect calculation of treated floor area, but others such as the existence of large computer rooms or catering facilities can also affect the NPI. Although the use of the NPI is recognised to provide rough, compressed, qualitative evaluation of buildings energy performance, it is still an accepted approach to conduct preliminary evaluation of offices, hospitals and local authority buildings energy performance.

There are other methods for building energy benchmarking using total annual energy consumption data. For example, the Display Campaign™ tool for assessing and displaying information on municipal buildings energy performance (Schilken & Magnin, 2005). The European Display Campaign™ is voluntary initiative launched by Energie-Cités to support the implementation of EPBD and to stimulate public display of information about energy performance in public buildings. The methodology for assessing building performance devised by the Display Campaign™ is based on a ratio between primary building energy consumption and gross internal floor area of the building. According to the building type (educational, administrative, etc) the performance is graded into a classification scheme of six classes: A to G similar to the certification scheme of household appliances. This is similar to the UK Display Energy Certificates (DEC), though building energy performance calculation for producing DEC is more complex and requires more data than just the annual energy consumption and building floor area (DCLG, 2008).

2.2.2. Building energy monitoring

Building energy monitoring in the sense of tracking building energy performance, is a logical improvement of benchmarking using annual data. Monitoring energy consumption can result in the analysis of seasonal weekly and daily variations and other energy consumption patterns. If sub-metering is available it is possible to disaggregate end-uses and acquire a greater insight on energy consumption profiles. An example of energy monitoring is building energy aM&T approach. As described in the previous section aM&T can be defined as AMR system with analysis capabilities based on M&T. The only required input for M&T is time-series monthly, weekly, daily or even sub-daily electricity and gas consumption data and determining factors, the variables that affect energy use. Time-series energy data can be acquired manually from electricity and fuel bills, meter readings and sub-meter readings, or automatically using AMR systems. Outside temperature is usually the most important variable that affects energy use in buildings, and can be modelled using degree-days or mean daily outside temperature.

The UK has developed several research and commercial M&T and aM&T hardware and software products. Evidence presented by Harris (1999) suggests that the first application of M&T to buildings in the UK was performed in 1979 in 200 hospitals, when degree-days were used to monitor energy consumption against set targets. Following this first study the Department of Energy set up a programme to develop and promote energy monitoring and target setting techniques.

A seminal book on M&T was published in 1989 (Harris, 1989). This book set the ground for the development of the energy M&T discipline in the UK. Another book by the same author, Harris (1992) describes a new approach on building energy and water management using M&T. More recently, Harris (1999) presents a summary of a significant number of case studies of building energy diagnostics using degree-days. The UK Government programmes on energy efficiency have also been offering general guidance on M&T, for example (DETR, 1998a, b), and more recently (Carbon Trust, 2007a, 2008). These guides advocate the application of M&T to buildings based on the calculation of degree-days energy signatures - also regarded as building energy performance lines.

Degree-days are a measure of by how much and for how long outside temperatures were above or below a given base temperature. Typically the base temperature is considered to be the building inside control temperature, which for simplicity is considered constant. In the UK the standard base temperature for calculating heating degree-days is 15.5ºC, though for health care buildings it is set in 18.5ºC. Correction factors can be applied to adjust base temperature in order to accommodate specific characteristics of building structure, occupancy and people's activity.

From (Harris, 1999) one can say that heating degree-days are of interest for energy management because of their application in:

- Assessing the heating needs of buildings for the purpose of designing heating systems;
- Adjusting energy consumption data for buildings for differences in weather for one year to another or due to location to enable comparisons and normalisation of performance indicators - NPI, and also to calculate ratings such as DEC;
- Forecasting of energy use for the purposes of budget preparation.
- Assess building weather related energy consumption;
- Evaluation of potential savings to justify investments in energy efficiency.

- Monitoring energy use by detecting and characterising faults in heating and cooling systems.

The last three apply to what is known as the building energy performance line, which is the graph of energy against degree-days usually, for monthly time series.

The building energy performance line can be understood as simple model for describing building energy consumption dependency from outside temperature. In fact, according to (ASHRAE, 2001) classification of building linear regression between energy and degree-days is a steady state inverse modelling technique, which can be used to breakdown between fixed heating energy consumption (standing losses and hot water heating) and weather related energy consumption. Here, inverse modelling can be understood as the opposite of building forward modelling, i.e. the simulation of building energy use taking only in consideration the physical description of the building systems or component of interest. Inverse modelling is a data driven approach that takes as input the output variables – for instance energy consumption and degree-days data. Inverse modelling aims at determining the mathematical description of the building and to estimate the system parameters. Note that instead of degree-days, outside temperature can also be used in model, as it is described later in this thesis.

Traditionally in the UK, building heating energy M&T is performed with degree-days, using the following equation:

$$\hat{E} = c + b_1(DD)$$

Equation 1. Degree-day building energy consumption model

In this equation, $\hat{E}$ represents the estimated monthly energy consumption and DD are the monthly heating degree-days. c is the non-weather related energy use and b_1 the regression line slope, which represents the dependency of energy consumption over winter.

After defining the mathematical relationship between energy use and weather, the next step in building M&T is the production of a control chart. A control chart is calculated from the residuals of the regression model, and can be defined as the difference between the real consumption E, and predicted energy consumption $\hat{E}$. Control bands can be applied to the residuals, and the resulting control chart can be used to alert for high or low energy consumption. Another control technique to detect uncommon high or low energy consumption is the CUSUM plot. CUSUM identifies changes in consumption pattern, using cumulative sum of the difference from standard performance. The use of degree-days, controls chart and CUSUM plots in building energy M&T is explained in detail by Harris (1989).

An energy performance line is a simple model of building thermal behaviour in relation to outside temperature. According to CIBSE Technical Memorandum (CIBSE, 2006b) performance lines are suitable for monthly data, but not to daily data. CIBSE (2006b) states that performance lines with daily data cover up non-linear building behaviour such as thermal capacity, occupancy and gains fluctuations from day to day. Additionally, the use of a fixed base temperature (15.5ºC) is also not free of criticism, and Day (1999) exposes the uncertainties on the theory of degree-days calculation, especially concerning the use of a fixed base temperature. Day is clearly in favour of the use of degree days in energy management, and just alerts to the fact that the established calculation method introduces errors that practitioners may not be aware of. Harris (2006) offers a review of (CIBSE, 2006b) guide, and points out several inconsistencies on the impact of a base temperature different than 15.5ºC. The debate around degree-day use on building energy managements continues, leading to the conclusion that the underlying theoretical grounds for the application of degree-days in energy management are not yet fully developed. However, in the USA, researchers and practitioners have been applying other methods to model the relationship between energy and outside temperature - the building energy signatures described in (ASHRAE, 2001) and elsewhere.

So, if daily data is available, building energy signature can be used instead of energy performance lines (monthly energy against monthly degree-days). Building energy signature is the plot of energy consumption against average outdoor temperature, for the same period, typically the day. This is much more adequate to the type of the data available for the research work presented here. Available half-hourly energy and outside temperature data can be aggregated into daily periods and be used to produce building energy signatures.

Building energy signatures can be defined using change-point models, as presented in ASHRAE's Inverse Modelling Toolkit (IMT). These single-variable models are able to capture the non-linear relation between heating and cooling energy use and outside temperature of different building types. A summary of IMT equations is presented in (ASHRAE, 2001), more details on IMT algorithm can be found in (Kissock, et al., 2003) and later on this thesis. These models can also be used to produce control charts and

CUSUM plots to be used on building energy M&T; however, no reference of such application was found in the literature.

An OC&C study (OC&C, 2004) on the adoption of aM&T systems in the UK uncover several opportunities for improving the energy analysis techniques and software tools currently in use. This study identified that research is necessary in M&T data analysis, support for data analysis interpretation and use data to improve building performance assessment and the identification of energy savings. The required improvement of aM&T systems effectiveness may be derived from experience on benchmarking and operational diagnostics using short time series data.

2.2.3. Operational diagnostics to improve building performance

Annual benchmarking and energy monitoring are useful in identifying inefficiency at the whole building level and focusing efforts towards large energy end-uses, while operational diagnostics allows detection of specific problems and helps target the causes of problems.

Operational diagnostics require more detailed data and building information than benchmarking and monitoring. Diagnostics involve the evaluation of specific system and component operations. Typically operational diagnostics are only possible in medium to large building equipped with BEMS, or after conducting a measurement campaign to acquire the required detailed data.

As described previously, diagnostics can be performed manually or automatically. Manual diagnostics are usually conducted by experienced practitioners with the help of time series visualisation and analytical techniques, while automatic diagnostics are performed by software packages with built-in models, statistics, and expert rules that support the detection and diagnosis of a series of operational problems.

Manual diagnostics are based on the visual inspection of BEMS data (short time series data energy, temperature, and other sensors). The most common data visualisation techniques for short time-series data are line graphs, or bar charts, 3D surface plots and 2D contour plots. Note that the effectiveness of manual diagnostics using visual techniques is strongly related to the energy practitioners' expertise and experience. A less experienced user may not have the skills to fully interpret the charts presenting building energy short time series data.

A review of time series visualisation techniques is presented in (Motegi, et al., 2003), a report on the features and capabilities of energy information systems for commercial buildings. This report presents a review of software packages for building energy management available in the USA, and includes a comprehensive review of time series visualisation techniques, including daily profiles, maximum and minimum analysis, 3D plots and calendar view profiles. It also includes a review of analytical visualisation plots, such as aggregated data summaries, breakdown by end-use, multi-site comparison and regression plots.

Table 3 presents (Motegi, et al., 2003) suggestion for visualisation techniques that can be applied to short time-series energy consumption (hourly and sub-hourly data), which can be used for manual diagnostics.

Table 3. Time-series visualisation techniques – adapted from (Motegi, et al., 2003)

Type	Data frequency	Graph types	Description
Daily profile	hourly or smaller interval	line plot (2D)	This is the most common short times series energy consumption data visualisation plot. It can be used to verify operation schedules, identify peak hours, and baseloads.
Day overlay	hourly or smaller interval	line plot (2D)	Overlay plots display multiple daily profiles on a single 24-hour time-series graph. Daily overlays are useful for finding abnormal days that would otherwise be difficult to find in a single daily profile.
Average	hourly or smaller interval	line plot (2D)	The average function calculates the average hourly (or less) energy consumption values for selected days and displays an average daily profile, which can be used for baseline reference.
Highs and lows	hourly or smaller interval	line plot (2D)	Indicates maximum and minimum hourly consumption values for the day, or plots a daily profile of the maximum and minimum day within selected days.
Point overlay	hourly or smaller interval	line plot (2D)	Display of multiple time series data points on the same graph, and it can be appplied to for multiple sites or equipments. It is also useful to overlay highly correlated data.
2D and 3D chart	hourly or smaller interval	contour (2D) and carpet (3D) plots	2D and 3D charts often display the time of day, date, and variable of study. These charts can be used to quickly determine which time-periods might be problematic, for example, peaks occurring at unexpected time.
Calendar profile	hourly or smaller interval	cluster plot (2.5D)	View of an entire month of consumption profiles on a single screen as one long time series. The calendar profile displays the historical sequences of daily profiles and weekly trends.

Concerning automated diagnostics to improve building performance, Motegi, et al. (2003) raises an interesting question on a common overstatement from commercial software packages marketing brochures, the assumption that software can automatically detect and diagnose system malfunctions. In fact, most of the energy analysis software packages only provide data visualisation and is up to the practitioner to interpret data in order to detect and diagnose potential faults. Motegi, et al. (2003) concludes by suggesting that more research is needed in advanced analysis techniques and automated fault detection and diagnostic of building energy savings.

As mentioned earlier, Brambley and Pratt (2000) explain that automated diagnostic tools use a combination of models, statistics and expert rules to detect operational problems.

Automated diagnostic tools are applied to the different building systems, but mainly HVAC. Therefore, automated diagnostics require several data inputs from BEMS and additional information from users. For example, an air handling unit diagnostics software module that was tested for a building in California and documented in (Katipamula, et al., 2003), refers to the fact that data collected on a continuous basis included at 5 minute-intervals: outdoor-air temperature, return-air temperature, mixed-air temperature, supply-air temperature, chilled water valve position, supply-fan status, outdoor-air relative humidity, and return-air relative humidity. Additionally, building occupants supplied information about the scheduled of use of each air handler. This automated diagnostic software is based on rules derived from engineering models and expert knowledge on relationship between input variables in normal operating conditions. The detected problems ranged from faulty sensors to badly positioned sensors, jammed dampers, unscheduled operations, excess or inadequate ventilation.

Model based diagnostics can be supported on past consumption data, to which measured BEMS data is compared and deviation from the model is assessed. The model can be based on means values derived from historical records, or based on single or multivariate regression models (energy, temperature, occupancy, etc.). Alternatively, model based diagnostics can be performed using a building simulation results (Piette, et al., 2002), for instance running EnergyPlus or other building simulation software to simulate the functioning of the building and possible BEMS system outputs, potential faults and corresponding diagnostics. This type of diagnostics requires complete description of the building envelope, building equipments and services.

The automated diagnostics concept was helpful for understanding the context where the current work developed. However, this thesis was focused in the use of short time series primary metered data to improve building operation, and not BEMS end-use data. Data available for this study was restricted to total electricity and total gas consumption in half-hourly intervals, outside temperature data, building type and floor area information. Therefore, benchmarking using annual data was possible, and the application of M&T techniques and some kind of manual diagnostics using visualisation techniques was also possible. However, according to the published literature, automated diagnostics require more than just primary meter short time series data. Nevertheless, this thesis investigated to what extent it was possible to perform diagnostics to building energy performance using only primary metered short time series electricity and gas data.

2.3. Conclusions

It is expected that primary meter short time series energy data from the increasing deployment of smart metering for electricity will be increasingly available. The main policy drivers for more increasing metering and monitoring of energy consumption in buildings are currently the implementation of European Directive EPBD and the ESD.

The analysis of energy consumption time series data on annual and monthly periods is considered to be an established procedure, though there are still some issues on the use of degree-days and energy performance lines. The use of existing annual benchmarking and M&T techniques is acceptable for annual and monthly data, respectively; however, this may not be the case for hourly or sub-hourly data. Research on the analysis of short time series building energy consumption data (in hourly or smaller intervals) has been based on manual and automatic diagnostic techniques applied to BEMS data.

Manual diagnostics are based on the visualisation of data. Visualisation of energy consumption data is also a well researched area, and these techniques have been applied successfully to the analysis of short time series data. The next chapter reviews the possibilities and limitations of the most common visualisation techniques, and enhanced visualisation capabilities achieved by the introduction of graphical indices (the use of statistics).

Apparently, automated diagnostics can at present only be applied to data generated by BEMS, because it requires energy, temperature, HVAC operation conditions, etc.. According to Katipamula and Brambley (2005) automated diagnostics to improve building systems operation is in its infancy, and therefore there are several opportunities for research and development. For example, more research is needed on automated diagnostics using less data inputs. This research aims at contributing to this purpose and to further develop the assessment of building consumption profiles using limited information: primary meter short time series electricity and gas data, outside temperature and limited information about the building type and floor area.

In summary, the current work adds to existing research by testing a new framework that characterises building electricity and gas consumption profiles using load demand profile indicators and parameters that model the relationship between energy and outside temperature. This allows for the comparison of similar buildings using standardisation and benchmarking analysis identified demand profile characteristics that can be indicative of potential energy saving opportunities. The approach tested can be automated and integrated as a module in existing software packages. Software currently uses short time series visualisation, which can then be combined with the new metric, to be described in chapter 6, to improve inference. The next chapter presents reviews the most important visualisation techniques mainly used by researchers and advanced practitioners.

Chapter 3. The case for short time series energy data visualisation

This chapter reviews visualisation techniques that can be applied to the analysis of primary meter short time series energy consumption data in buildings. Examples of the application of each technique to real buildings are presented. The purpose of this chapter is to review the state of the art in visualisation of times series energy data and how visualisation can be used to assess building performance, detect and diagnose faults to optimise building operation.

From the literature available, two review papers on visual analysis of short time series electricity consumption data (Haberl & Abbas, 1998a, b) standout. These papers present a detailed evaluation of the analysis of hourly electricity data using 3D surface plots, weekly totals line plots, 24-hours profile plots and x-y plots. These techniques have been applied to the analysis of metered hourly electricity consumption data from government buildings in the Texas LoanSTART programme for energy efficiency. Haberl and Abbas (1998a, b) suggest that visual techniques can be improved by adding graphical indices to the line plots. These graphical indices provide additional information about changes in consumption patterns over a period of data, typically a year. Different data visualisation techniques that can be applied to short time series energy consumption data were reviewed, in particular:

- 3D surface plot, for 1 year of data, an appealing format to display all data points in a single plot;
- 2D contour plots, for 1 year of data, similar to the latter, but using a 2D view.
- Monthly, weekly and daily line plots, which provide an overview of the seasonal pattern of consumption in different resolutions;
- Average daily profiles line plots for actual and average consumption, useful for understanding the energy consumption pattern over 24 hours.

3.1. 3D Surface plot

Three-dimensional surface charts display the time of day, date, and the variable for study – in our case half-hourly electricity or gas consumption. These charts can be used to quickly overview data. For example, a 3D chart might indicate peaks occurring at unexpected time periods over a month or a year. An energy manager finding an unusual feature in a 3D chart can then study a daily profile in more detail, or examine other graphs for that period. 3D chart are useful for a top-down manual diagnostic approach, and can be used complementary to other visualisation techniques.

Christensen (1984) reviewed the development of graphical displays and traced the development of 3D graphic plots. Christensen and Ketner (1986) proposed for the first time the use of Energy Maps – EMAPS – coloured contour plots for the analysis of hourly series building simulation results. The application of 3D surface plots to building energy management has been discussed in detail on Haberl and Abbas (1998a), where they concluded that these charts are useful for the rapid display of large amounts of hourly building energy consumption data. The authors continue and state that 3D surface plots can qualitatively display peak energy consumption, daytime and weekly extreme variations, seasonal patterns and periods of missing data. In Wijk and Selow (1999) 3D surface graphics, complemented by calendar view techniques, are applied to the analysis of hourly electricity consumption of the ECN building in the Netherlands. These graphic experts say that such plots are useful to show all data simultaneously, and that can be used to distinguish seasonal trends, as well as daily patterns. However, they state that 3D surface plots have limitations when distinguishing variations over the week. Another limitation pointed out by Wijk and Selow is the elimination of the fine details by the 3D surface smoothing effect.

The next figure presents a 3D chart produced in the current work. The objective of producing these graphs was to acquire a visual impression of a full year of half-hourly energy consumption data, and test it using available data.

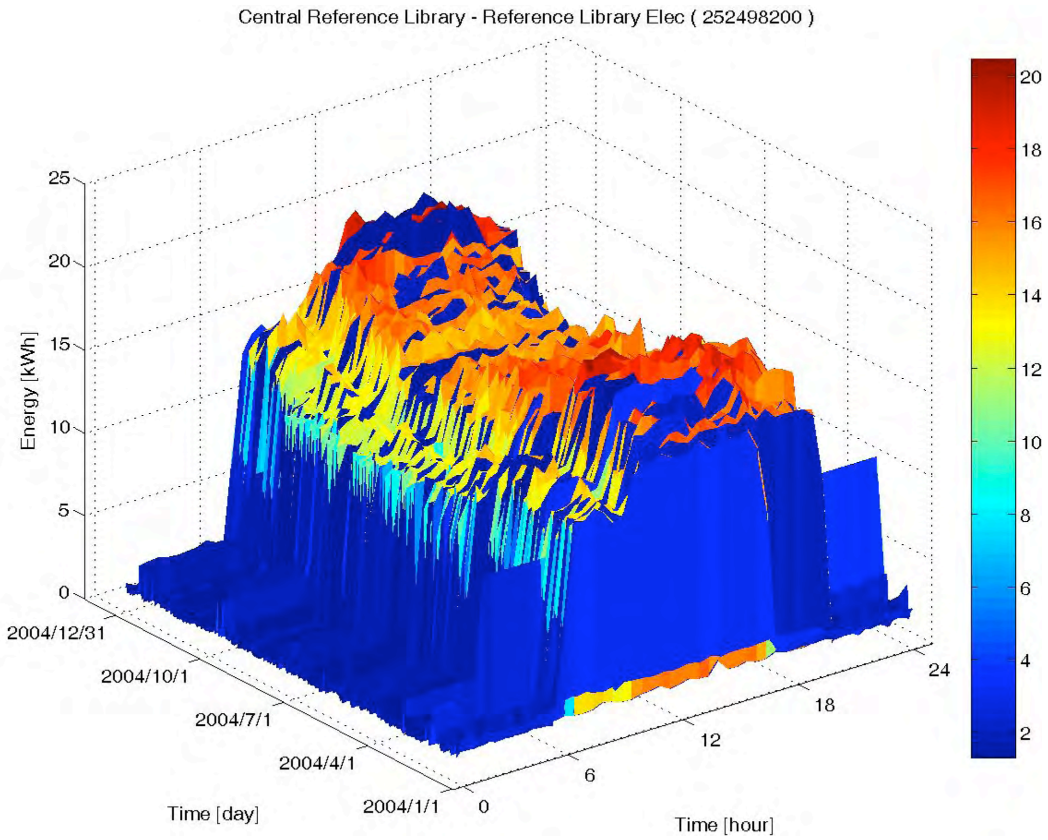


Figure 3. 3D surface chart presenting one year of energy consumption data

From the 3D chart for 2004 electricity consumption of Leicester Central Reference Library it is possible to detect a seasonal variation of electricity use, high in winter and lower in summer. It is also possible to get an impression about the daily profile. However the three-dimensional nature of this graph conceals some details, and makes the data interpretation difficult. Alternatively, 2D contour plots are considered a more simple and easy display of short time series energy data. These 2D plots are a projection of 3D plots into the X-Y axis.

3.2. 2D Contour plot

The next figure presents the 2D contour plot for the same building and similar period, as the previous figure.

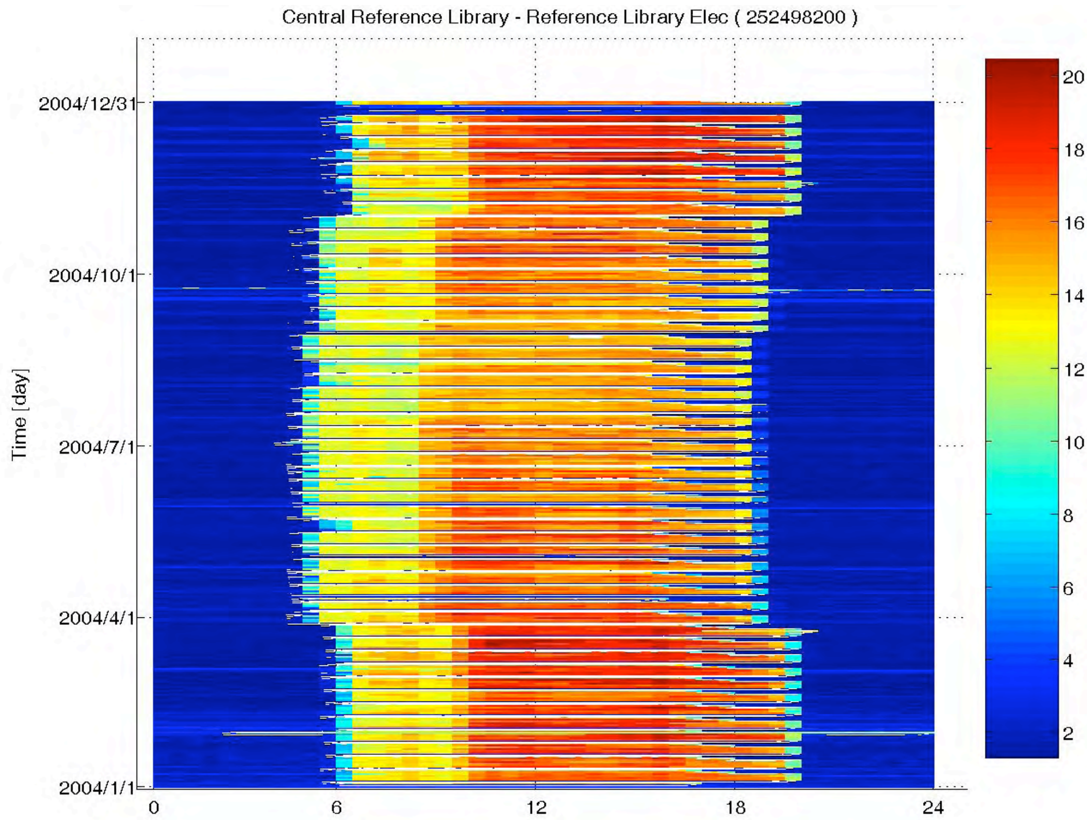


Figure 4. 2D Contour plot presenting one year of energy consumption data

From the half-hourly electricity consumption displayed using a contour plot it is possible to identify not only the seasonal variation, but also the periods of high and low energy use. Unusual consumption outside normal operating hours is also visible in a few occasions in Figure 4, Central Reference Library 2004 half-hourly electricity consumption data.

In the current work the 2D contour plots were found to be useful to the identification of missing data, and to select data sets for analysis. These 2D contour plots, although not so visually striking, are more sensitive to the fine detail of missing data, daily and weekly variations than 3D surface plots. Therefore 2D contour plots were found to be more useful for visualising the large data sets under analysis.

The first reference to 2D contour mapping for displaying half-hourly electricity data in published energy management guidance in the UK is (DETR, 1998c) and (Vesma, 2000). Ferreira (2002) used 2D contour plots, 24-hour profile and weekly profiles to analyse one year of primary metered half-hourly electricity consumption in eight office buildings in Leicester. This study refers to contour mapping as a technique that provides a visual impression of the seasonal, weekly and daily cycles occurring throughout the year. It is said to be a method that allows the display of several months or even years of actual half-hourly data, and that it is a simple technique for spotting daily and sub-daily periods of excessive consumption, occurrence of untypical consumption and variation of demand patterns. Similarly, Stuart (2004) presents one year of half-hourly data from school buildings displayed in a MS Excel 2D surface chart.

Another interesting application of 2D contour plots is the analysis of short time series energy consumption data from HVAC systems data to optimise operation and reduce energy consumption. This approach presented by Isakson and Eriksson (2004), uses contour plots, to browse BEMS historical records of short time data (electricity, temperature, humidity, etc). This data browser was developed in a Matlab® application (Mathworks, 2008). Similarly Baumann (2003, 2006), presents the use of 2D contour plots in building operation diagnostics - a method for optimization of building operation using BEMS data. This method has been developed with the support of the International Energy Agency task: Implementing Agreement Energy Conservation in Buildings and Community systems, Annex 40 - Commissioning of Building HVAC Systems for Improved Energy Performance (Visier, 2005).

3.3. Line plots for presenting monthly, weekly and daily data

Line plots are the most common presentation of time-series energy data. Figure 5 presents the line plot of mean daily consumption for electricity consumption in an example building (Central Reference Library in Leicester) for twelve months of 2004. The plot presents the (arithmetic) mean electricity consumption for twelve months, complemented be the maximum and minimum daily electricity use for each month. The blue line represents the mean value, i.e. the daily mean electricity use for each month. The red line represents the daily maximum value, and the green line represents the daily minimum value for each month. From the monthly plot it is possible to extract information about the annual variation in the mean energy consumption, and the corresponding maximum and minimum values. For Leicester Central Reference Library, the mean and maximum consumption in winter months is higher than in summer months. However, the minimum consumption (which probably occurs on weekends and holidays) is relatively constant over the year.

A similar line plot can be produced for weekly periods. These are similar to monthly plots, but weekly mean, maximum and minimum values for a year are calculated instead. Figure 6 presents a line plot for the mean daily energy consumption for Leicester Central Reference Library, calculated for the fifty-two weeks of 2004.

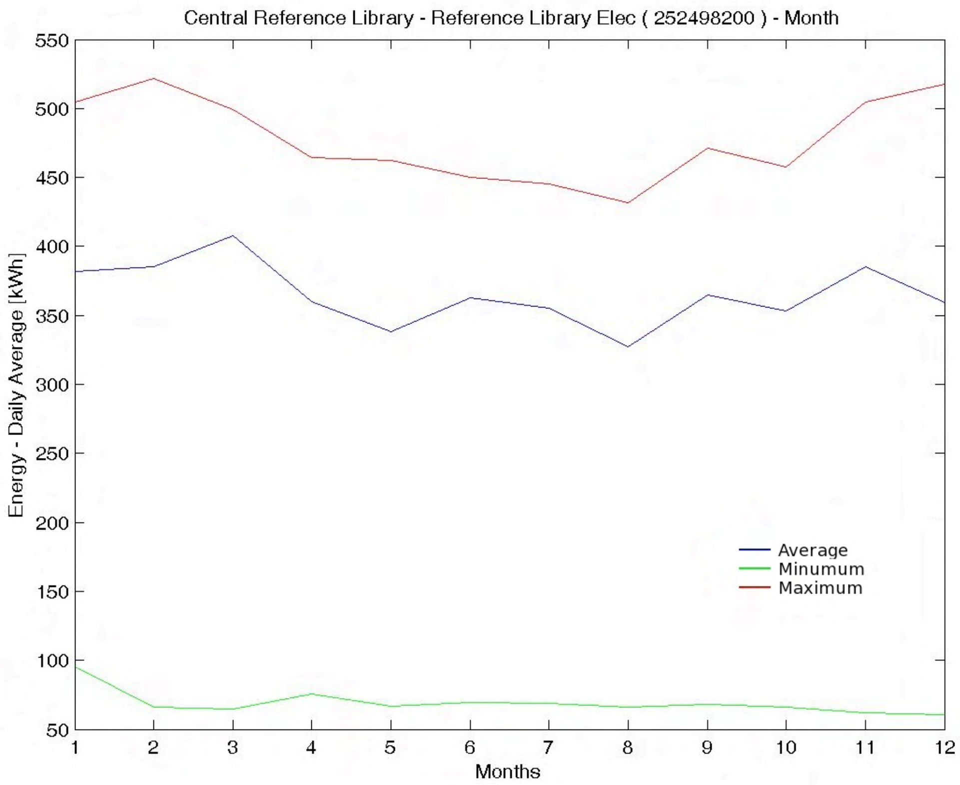


Figure 5. Example of monthly energy consumption line plot

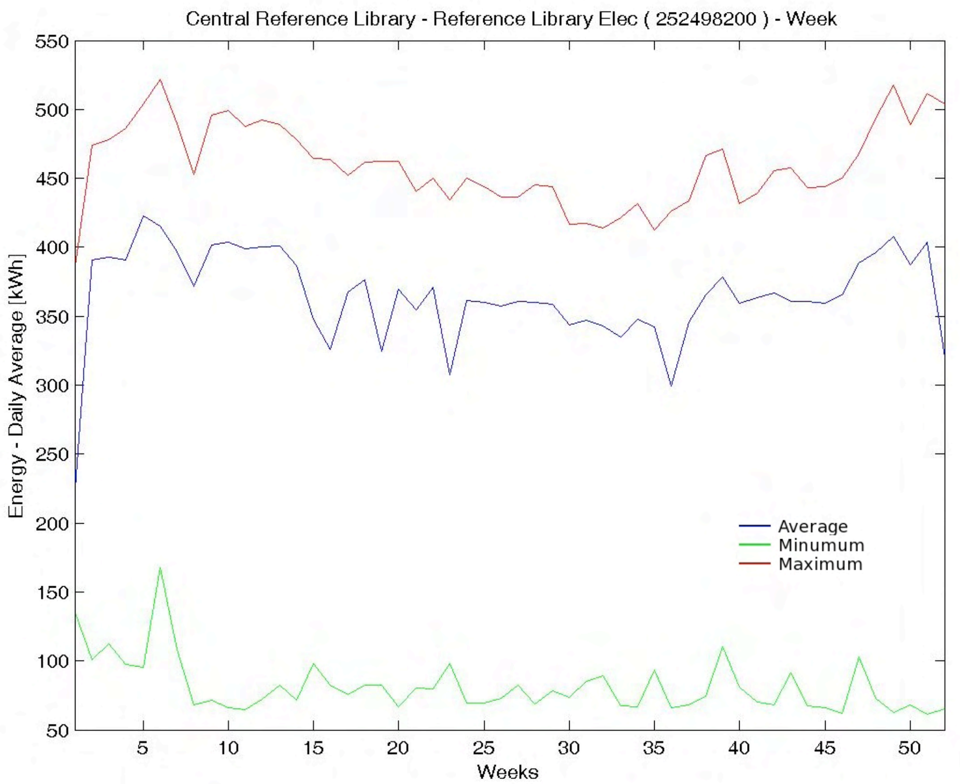


Figure 6. Example of weekly energy consumption line plot

From the weekly line plot is possible to extract information about the seasonal variation of energy use over a year, with greater detail than with the monthly line plot. The weekly line plot presents a breakdown for the fifty-two weeks of the year, in which it is possible to identify weeks with holidays and breaks. For the Central Reference Library plot above, it is possible to identify the New Year break, the Easter break (weeks 15 and 16), May Day (week 19) and spring break (week 23). The 30th August holiday on week 36 week, and of course the Christmas break. The mean values are lower in weeks with holidays and breaks. However, maximum and minimum values are not affected significantly on those weeks.

In summary, it is possible to say that monthly and weekly line plots describe the variations in consumption over a period of time, in this case a year, but very little can be said about opportunities to reduce energy use.

The alternative to monthly and weekly total energy consumption line plots is using actual values instead of mean values. However, the use of actual values is more limited, because plots presented earlier based on mean values provide additional information for data interpretation, for example the maximum and minimum daily energy consumption and allow the introduction of graphical indices, described later in this chapter, which add more insight to the analysis of time-series energy data. Nevertheless, these plots provide very limited information that can lead to the identification of potential energy savings. The monthly and weekly line plots are visual aids that support the acquisition of information about seasonal, monthly and weekly variations in building energy consumption.

This is also the case for the total daily energy use for a year of data, presented in Figure 7 for the Central Reference Library. This plot provides a simple overview of the actual energy use in the building and how it varies over a year. The lower points of the line correspond to the energy consumption on weekends.

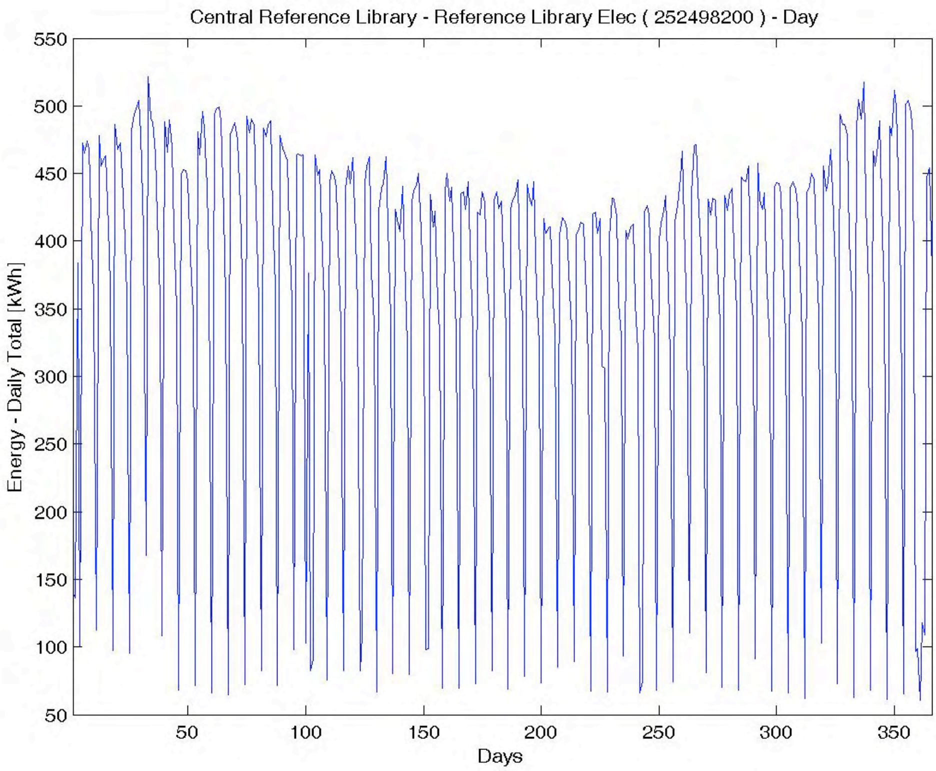


Figure 7. Example of daily total energy consumption plot

3.4. Line plot for daily half-hourly data – the load demand profile

The use of load demand profiles is more effective in capturing the variations over the 24 hours, calculated for a single day (actual consumption) or over a period (average consumption) than the plots presented so far.

The half hourly energy consumption values for selected days are displayed in a line plot for a given period (set manually by the user). The x-axis is set to one day, 24-hour, and the plot includes 48 data points, one for each 30 minutes intervals, presented in Figure 8.

The daily half-hourly profiles can be plotted for actual consumption on single days; alternatively it is possible to calculate mean half-hourly energy consumption values for set periods, for example one year. Daily energy consumption profiles, also regarded as load demand profiles or power signatures, have been used for quite some time in building energy management. The first reference found on this topic was by Reiter (1986), who investigated the importance of scheduling in the determination of total electricity consumption and the temporal distribution of end-use consumption. This study was based on hourly load profile for two commercial buildings in the USA. MacDonald and Akbari

(1987) used building characteristics, monthly and hourly electricity data for assessing the energy performance of commercial buildings in the USA. They state that hourly power profiles provide additional detail, and that they can be applied for understanding the potential and the application of energy efficiency improvements in the commercial sector. In (MacDonald, 1988) the use of power signatures (or load demand profile) is suggested as an important concept for building energy analysis. He states that practitioners could improve their understanding of the building energy behaviour if they start using power signatures to analyse data and communicate results.

A comprehensive review and evaluation of techniques for analysing metered energy consumption in building is presented in (MacDonald & Wasserman, 1989). This study was done for Existing Buildings Efficiency Research program of the US Department of Energy. They refer to the use of power signatures as a useful energy analysis technique, and suggest that it could be applied for different day types, such as weekdays and weekends. MacDonald and Wasserman (1989) also suggested the use of mean/average power signatures over different periods, two weeks, a month, or even a year. Haberl and Komor (1990) in their paper 'Improving energy audits: How daily and hourly consumption data can help', assessed the performance of commercial buildings based on the analysis of whole-building metered hourly electricity data, temperature measurements, and data gathered from site visits. For each of the three buildings analysed, daily and hourly presentations of the data were considered to discover possible energy conservation measures. They conclude that metered data can and the correct visual techniques can help the analyst to perform an energy audit and to identify and diagnose problems that lead to energy cost savings.

Assessing building performance and identifying potential energy savings in buildings is the objective of the current work. Therefore, load demand profiles were included in the analysis of available primary metered short time series energy data. The half-hourly load demand profile plots can be produced for:

- Actual and mean profiles for set periods, typically the year;
- The mean profiles can be calculated for all days, or just for weekdays or for weekends.

The graph in Figure 8 presents the mean load demand profile (blue line), maximum values (red line) and minimum values (green line) for all the days in 2004. Maximum and minimum plots are respectively the higher and lower values found for each half-hourly data point. These can be useful to determine the boundaries of building energy usage, how high and how low is consumption during a day over a period of time, in this case a year. However, it is also informative to breakdown demand profiles between weekdays and weekends. Figure 9 presents the mean load profile calculated only for weekdays and Figure 10 the mean load profile only considering weekends days in 2004. This breakdown was introduced in order to identify the operational differences over the working days or weekdays, considered to be Monday to Friday, and the weekends – Saturdays and Sundays.

From the load demand profiles in figure above, it might be possible to visualise different features that can be indicative of potential energy wastage. For instance, the baseload consumption is around 2 kWh per half-hour (which is equivalent to a load demand of 4 kW), on weekdays, in Figure 9, and also on weekends, in Figure 10. When the baseload is compared with the peak demand, which is above 15 kWh for weekdays, and around 8 kWh for weekends, it appears to be low. However, there is no standard load demand profiles to compare against, and therefore is not possible to confirm that the baseload is in fact low. The same occurs for the peak demand values. Other information that can be extracted from the load demand profiles is the operational schedule. From the electricity profile for Leicester Central Reference Library it is possible to see that consumption starts to increase at around 5h00 and is reduced by 19h00 on weekdays. Comparing this schedule with the library opening hours can provide information about equipments switched on before time and equipments left running out of hours.

The comparison of weekdays against weekend load demand profiles can also be useful. From the load demand profiles above, it is possible to conclude that the Central Reference Library is probably open on at least one day on weekends. In fact this library is open on Saturdays until 16h00.

Load demand profiles can include additional descriptive statistics, and not only maximum and minimum values. Graphical indices based on percentiles can provide additional insight on daily load demand profiles, but also on monthly and weekly plots.

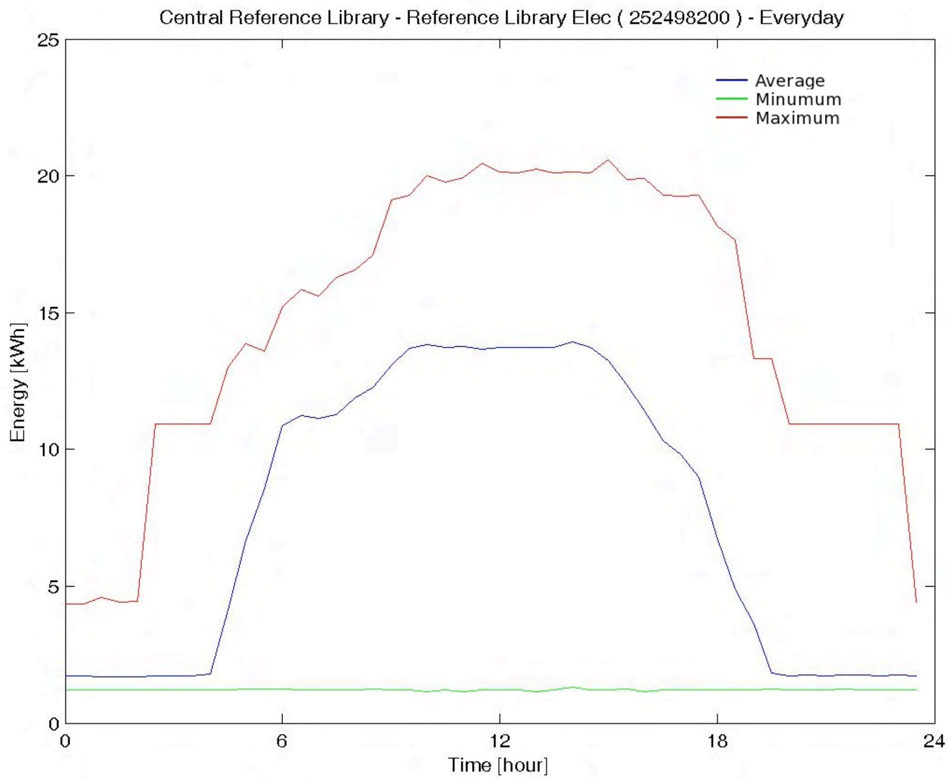


Figure 8. Mean energy load demand profile – Everyday

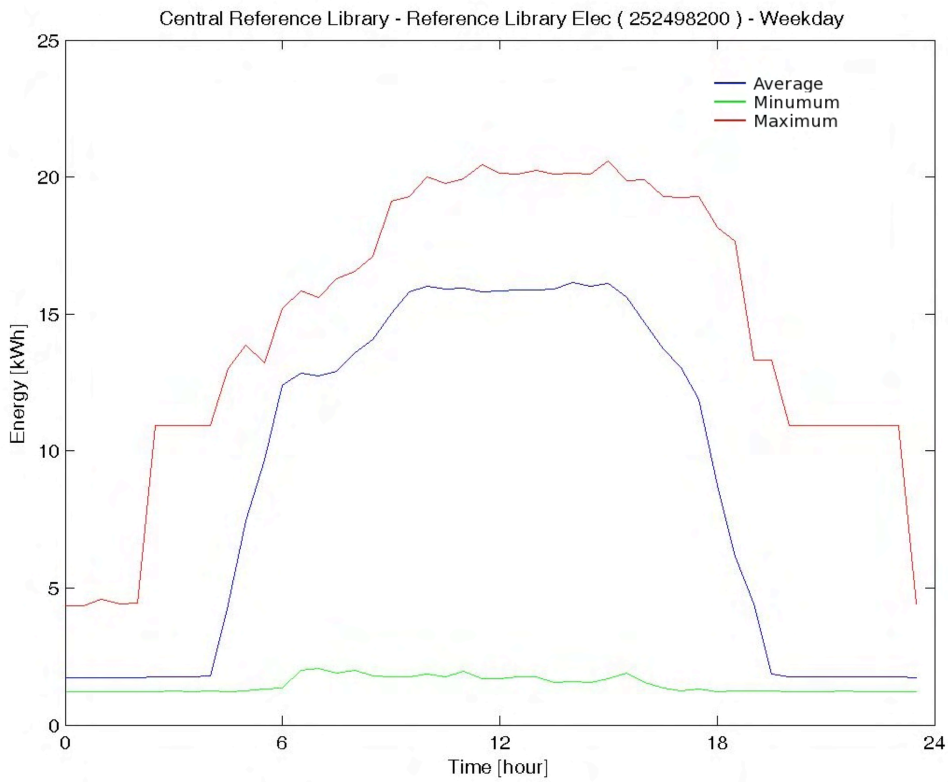


Figure 9. Mean energy load demand profile – Weekday

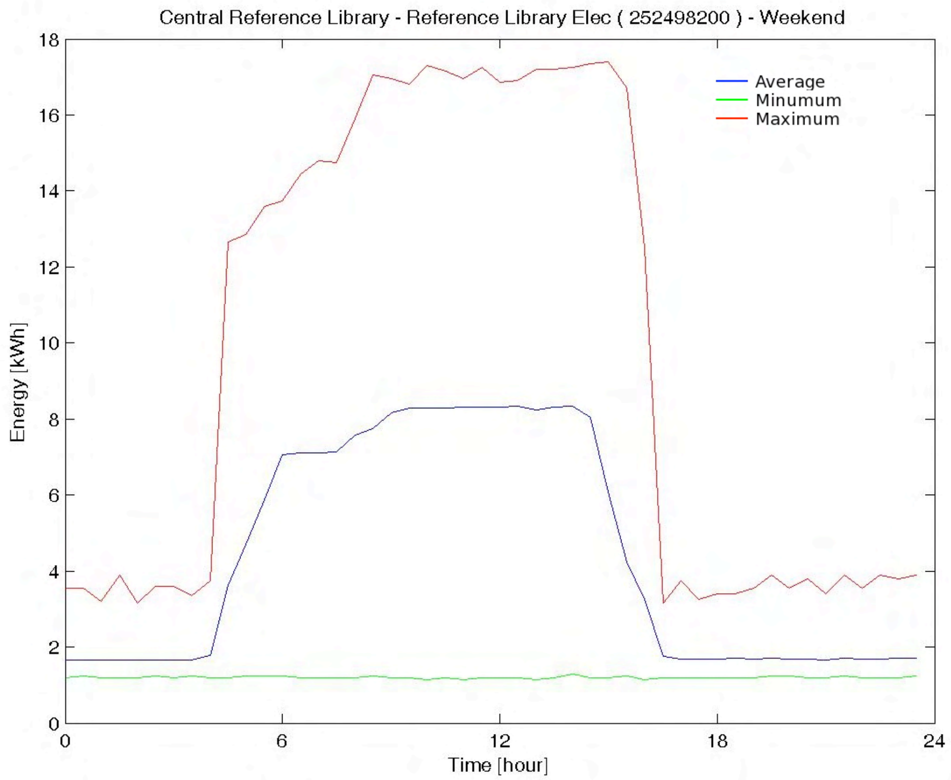


Figure 10. Mean energy load demand profile – Weekend

Alternatively, a 7-day load demand profile is also common, examples of these plots can be found in (Ferreira, 2002, 2003). The weekly load demand profiles plots have the advantage of providing information about individual days of the week, i.e. the demand profiles for Mondays, Tuesdays, Wednesdays, etc. However, it was found to be more efficient to limit the analysis to weekdays and weekends, i.e. two load profiles, instead of seven. Note that this may not be suitable for buildings with more than two patterns of occupancy. However, the introduction of graphical indices provides additional insight on the variations within the five days the week, Saturdays and Sundays. The integration of graphical indices calculated from percentiles in monthly, weekly plots and load demand profiles, is presented in the following section.

3.5. Graphical indices from percentiles

Although graphs are useful for presenting information and quickly identify consumption patterns, the interpretation of data using only plots is always subjective. This is more so for untrained energy managers. Chambers, et al. (1983) and Cleveland (1985) worked on the graphical perception and display of large amounts of time-series data. They found that graphical indices enhance the extraction of quantitative information encoded in a graph. Graphical indices can be the mean, maximum, minimum, standard deviation, median and percentiles. These indices provide quantitative information using a visual display. The box plot method introduced by Tukey in 1977, and published in his collected works Tukey (1994), and in (Tufte, 1983). A reviewed box plot was offered by Tukey (1990) which has been the basis for the Box, Whisker and Mean (BWM) plots produced by Haberl and Abbas (1998a, b) for the analysis of electricity consumption from Texas government buildings. These papers include only BWM plots for 52-weeks time periods and for hourly electricity profile plots.

In the current work, line plots are used to represent the graphical indices. The maximum and minimum values were kept as presented before. Figure 11 offers a legend for the graphical indices presented in the plots below that include mean, standard deviation, 10th, 25th, 50th (or median), 75th and 90th percentiles.

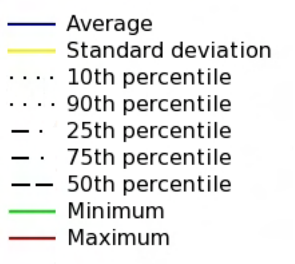


Figure 11. Legend for plots with percentiles

The mean is the blue line, and the yellow line represents the standard deviation from the mean, i.e. the root mean square deviation from the mean daily consumption. The dashed lines represent the median, or the 50th percentile.

The dotted lines represent the 90th percentile, if above the median, and the 10^{th} percentile if below the median. The dashed/dotted line represents the 75th percentile, if above the median, and if below the median the dashed/dotted line represents the 25th percentile. Examples of the application of graphical indices to visualisation techniques are presented in the next section.

3.5.1. Monthly plots with graphical indices

The plot in Figure 12 presents the Central Reference Library monthly electricity consumption data, in terms of daily mean, standard deviation, maximum, minimum and percentiles for the twelve months of 2004.

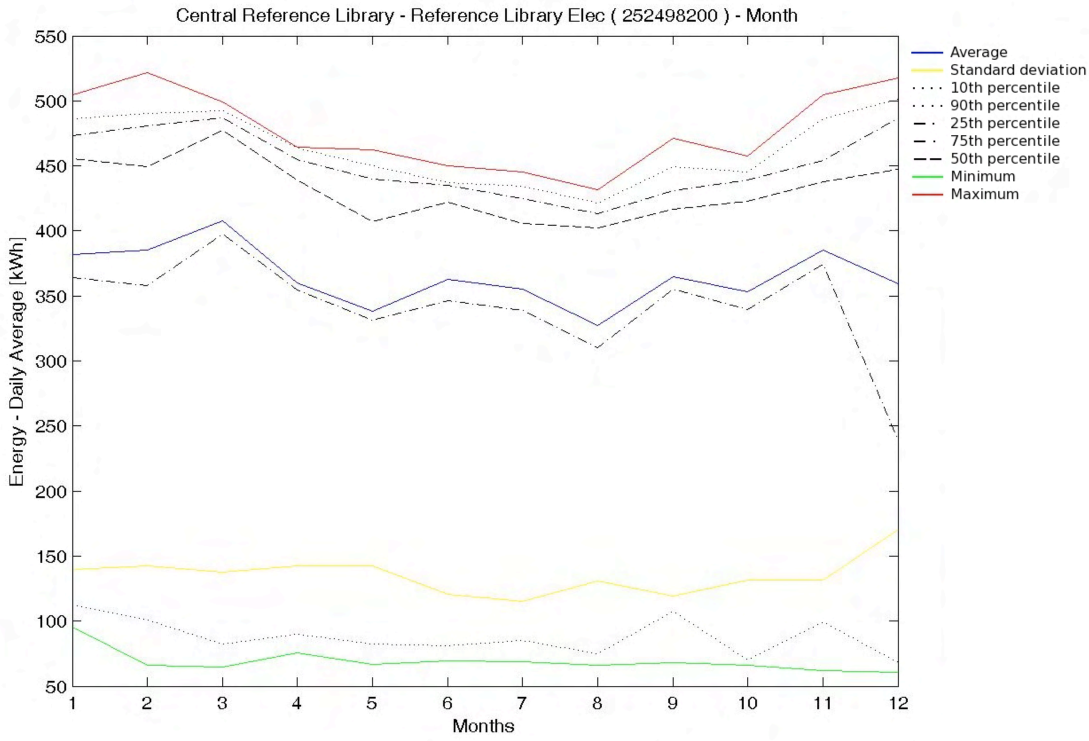


Figure 12. Example of monthly energy consumption plot with graphical indices

The p-th percentile of N ordered values was obtained by:

1. Calculating rank n, using the following equation:

$$n = \frac{N}{100} p + \frac{1}{2}$$

Equation 2. P-th percentile rank calculation

2. Using linear interpolation between the two nearest ranks, and taking the value that corresponds to that rank.

The 10th percentile represents 10% of the days with the lowest energy consumption. The 10th percentile (p=10), calculated for a month of 30 days (N=30), corresponds to rank of 3.5. Linear interpolation is conducted to find the value between the rank 3 and 4, i.e. the value between the third and the fourth days of the month with lower consumption. For the Central Reference Library monthly plot above, the 10th percentile is calculated based on energy use on Sundays. Similarly the 25th percentile for a month with 30 days corresponds to the eighth day of the month with lower consumption, which for the plot above would be probably a Saturday. Similar logic can be sought for the calculation of the 50th, 75th and 90th percentiles.

From the monthly energy consumption plot above it is possible to see that the median (50th percentile) is well above the mean, this is mainly because the mean is affected by lower consumption values on weekends and holidays. Another feature visible in Figure 12 is the proximity of the 50th, 75th and the 90th percentiles, from which is possible to conclude that the differences between consumption on working days are not significant.

The following section presents the introduction of graphical indices on weekly plots.

3.5.2. Weekly plots with graphical indices

As presented before, weekly plots are calculated using aggregated weekly data and daily totals. The weekly mean daily energy consumption (blue lines), maximum and minimum consumption (red and green lines respectively) were complemented with the standard deviation from the mean (yellow lines) and the percentiles values for each week. Figure 13 presents the weekly plot with graphical indices for the Central Reference Library.

The week consists of 7 days, and the Central Reference Library is occupied for about 6 days (note that Saturdays has reduced opening hours). The median (50th percentile) corresponds to the fourth day with lower energy consumption, which is a working day for most of the weeks in the year. From the plot it is possible to see that the median, and the 75th and 90th percentiles are very near. However, the 25th percentile is more distant. The distance between the 25th and the 50th, 75th and 90th percentiles are related to the spread between daily total energy consumption on weekends and on weekdays, respectively.

The relative position of the mean and the median (50th percentile) is related to the operation schedule of the building. For example, the mean value is close to the 25th percentile, however, for weeks with holidays and breaks the mean is closer to the 50th percentile than to the 25th percentile. It is possible to see that the mean values do not vary as much as the 25th and the 50th percentile. Though the mean values take into account the weekly variations, however these variations are smoothed when compared with variations experienced by the 25th and the 50th percentiles weekly values.

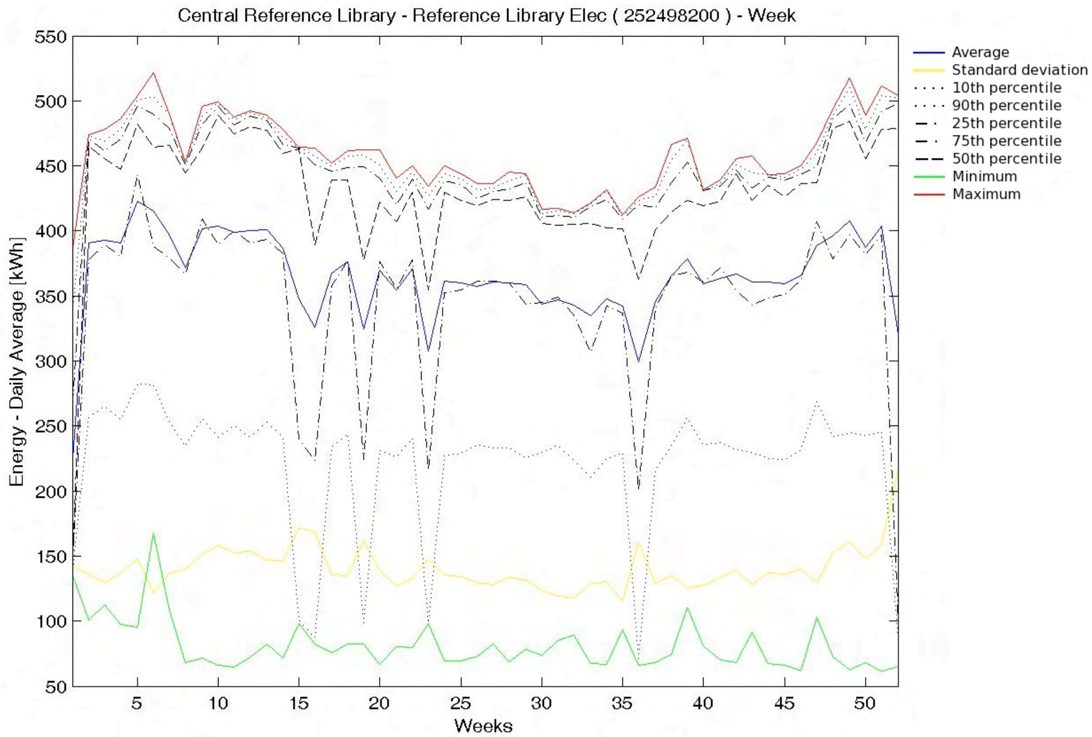


Figure 13. Example of weekly energy consumption plot with graphical indices

In summary, it is possible to state that monthly and weekly plots with graphical indices provide information that is related to the occupancy patterns of the buildings; seasonal variations over a year, differences between energy consumption on weekdays and weekends, and even the influence of holidays and breaks.

The next section applies graphical indices and percentile analysis from aggregated data (on monthly and daily periods) to the half-hourly data, through the use of 24-hour load demand profiles.

3.5.3. Load demand profile with graphical indices

The load demand profile presented in Figure 14 was calculated using the half-hourly data for 261 weekdays, a total of 12,528 data points. The blue line corresponds to the mean values for each half-hour of 2004 weekdays. Standard deviation, percentiles and maximum and minimum values were also included in the load demand profile plot for Central Reference Library electricity consumption.

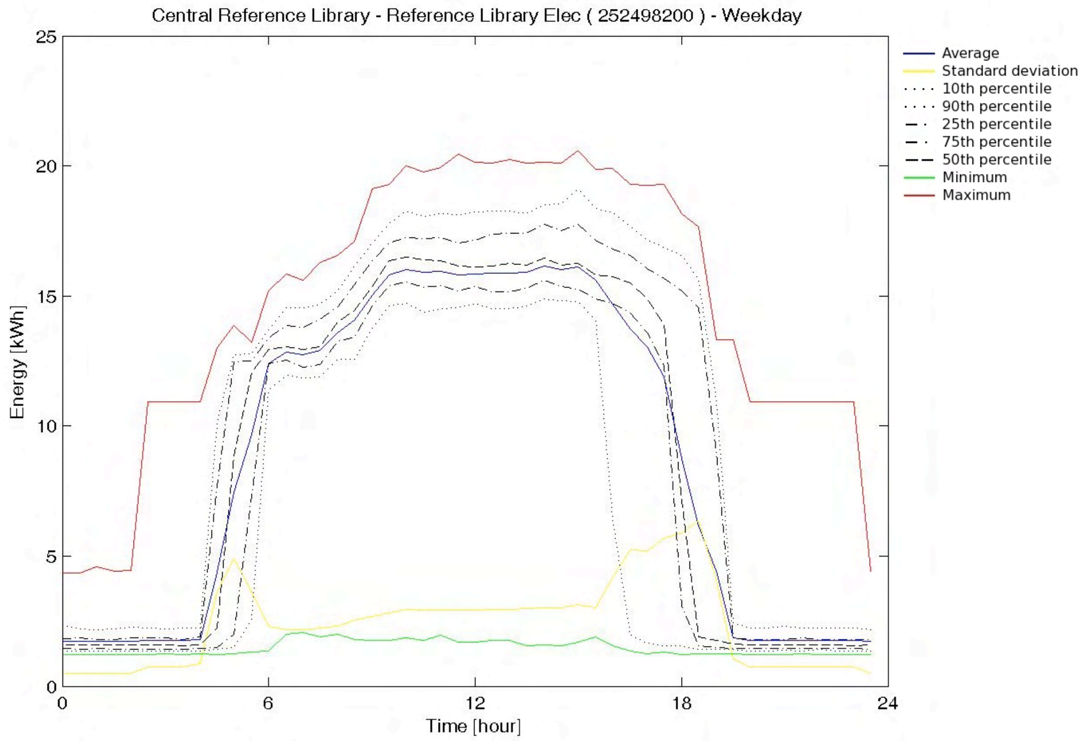


Figure 14. Example of energy load demand profile with graphical indices

Similar plots were produced considering all the days of the year, and another plot just considering weekends.

The use of graphical indices within the load demand profile provides more insight on the building operation. From a load demand profile plot the graphical indices have the following interpretations:

- The 90th percentile is a good descriptor of peak load, even better than the maximum demand profile;
- The 10th percentile denotes the energy consumption profile on weekends and on holidays;
- The consistency of building operation can be described by observing the distance between the 25th and 75th percentiles. The closer the 25th and the 75th percentile are, the more consistent is building operation over the year.
- The median values can be used to represent a typical load shape for a particular building.

For the example load demand profile plot with graphical indices for the Central Reference Library, presented above, it is possible to say that electricity consumption was well controlled over the year (the percentiles are relatively close). The mean profile appears to incorporate all the variations of the 'actual' profiles presented by the percentiles.

The interpretation of this plot would probably gain from an in-depth discussion with the building manager or even with building occupants. The causes of the variations between the percentiles are related to characteristics of the building behaviour. A site survey could also provide additional information for the interpretation of data. However, this is out of the scope of the current work, which aims at using only primary metered half-hourly electricity and gas data to assess building performance and infer the potential energy savings that can be achieved by improving operational requirements and reducing wastage.

3.6. Chapter summary

This chapter presented the main types of visualisation techniques suited for short time series energy consumption data.

Firstly, the application of 3D surface and 2D contour plots was presented. These plots are constructed using actual half-hourly data points. Surface and contour plots provide a visual impression of the seasonal, weekly and daily cycles occurring throughout the year. Using these techniques it is possible to identify daily and sub-daily periods of excessive consumption, occurrence of untypical high or low consumption and the general variation of demand patterns.

Secondly, the application of monthly, weekly and daily line plots was discussed. These plots are based on aggregated data, in monthly, weekly and daily periods, and on the use of mean daily energy consumption values. Therefore they hide the full information contained in half-hourly time series. However, they provide a clear overview of the seasonal pattern of consumption in different resolutions, and even more information when complemented with additional statistics contained in the graphical indices. For instance, the impact of holidays and breaks, the differences in total consumption between weekdays and weekends, and the impact of these changes in the calculated daily mean energy consumption values.

Thirdly, daily load demand profiles line plots were presented for annual mean data. These plots are useful for understanding the consumption patterns over 24 hours, on weekdays and on weekends. For instance, these plots can be used to determine the occupancy hours, the baseload and maximum demands on different periods, but also morning, lunchtime and afternoon energy demand. The percentile analysis provides additional insight to the energy consumption behaviour of the building. The percentile analysis applied to load demand profiles is useful for estimating peak loads, typical and mean load profiles, and the consistency of building operation over a year.

From the examples above it is possible to state that important characteristics of the building energy consumption pattern can be asserted from the interpretation of monthly, weekly and 24-hour load demand plots with graphical indices. Therefore, the introduction of graphical indices based on percentiles is by itself an important contribute to energy managers' current practices.

In summary, the visualisation techniques presented here are suitable for to the analysis of short time series energy data, even more when percentiles - graphical indices are integrated in the plots. However, the subjective nature of visualisation hinders the full potential of primary meter short time series data for building energy performance assessment and detection of energy potential energy savings. Therefore, manual diagnostic using visual techniques should be complemented with numerical analysis, using mathematical and statistical models, metrics and indicators that allow the measurement and quantification of building energy consumption profiles, using half-hourly time series data. Visualisation can then complement the interpretation of models and indicators. Chapter 6 presents a set of indicators that can support the automation of building 'automated' diagnostics using primary energy meter half-hourly building consumption data.

Chapter 4. Metering and monitoring in European local authorities

In chapter 2 and 3, in the literature review it was found several techniques, some more advanced than others, which are being used or can be used to analyse short time series data. In this chapter 4, it is present an overview of the results of a questionnaire survey of building metering and monitoring practices in European local authorities. The main findings presented in this chapter were published in ECEEE 2009 summer study proceedings (Ferreira and Fleming, 2009).

The aim of this exploratory survey was to complement the literature review, and get more information on current metering and monitoring best practice in European non-domestic buildings. The survey offered a characterisation of water and energy metering and monitoring technology and techniques, and identified the needs of building energy managers in the field. The preference for local authorities was usually because they manage a large portfolio of non-domestic buildings. In fact, the data used in this research project comes from Leicester City Council, a local authority that installed an automatic metering and monitoring system in about 300 buildings. The results of this survey provided valuable information for the definition of the energy analysis approach, and the development of the data analysis approach suggested by this research, which is presented in chapter 6.

4.1. Survey planning, preparation and delivery

The online questionnaire survey was developed and distributed to European energy managers. The questionnaire survey is presented in appendix. It was considered the most appropriate way of collecting information on building energy and water metering and monitoring practices. The questions were devised and analysed based on previous research such as (Converse, et al., 1986; Reeves, et al., 1981; Sekaran, U., 1992; Rothwell, 1998). Since this was a qualitative study, error margins were not the key issue for this survey, and the sample size only needed to be large enough to ensure a wide variety of answers from different countries. Therefore 20 to 30 replies might be enough (Rothwell, 1998), to get qualitative information on the metering and monitoring practices in European local authorities. All the answers were from voluntary respondents who were informed about the survey through different European networks of cities and municipalities active in sustainability, climate change and energy issues, such as Energie-Cites (www.energie-cites.org), the European office of ICLEI - Local Governments for Sustainability (www.iclei-europe.org) and CEMR, the Council of European Municipalities and Regions (www.ccre.org). Therefore the local authorities that responded to this survey can be considered to be very active in energy management, when compared to other European local authorities. Consequently the results presented here are biased, and may be considered to be amongst the best practice in Europe.

The survey had 76 respondents in total, from 19 European countries, as presented in Figure 15. About 39% of the respondents were from the UK, this was because the questionnaire was only available in English and not in other languages. In total, the respondents said to be responsible for managing energy and/or water consumption in nearly 63 thousand municipal buildings.

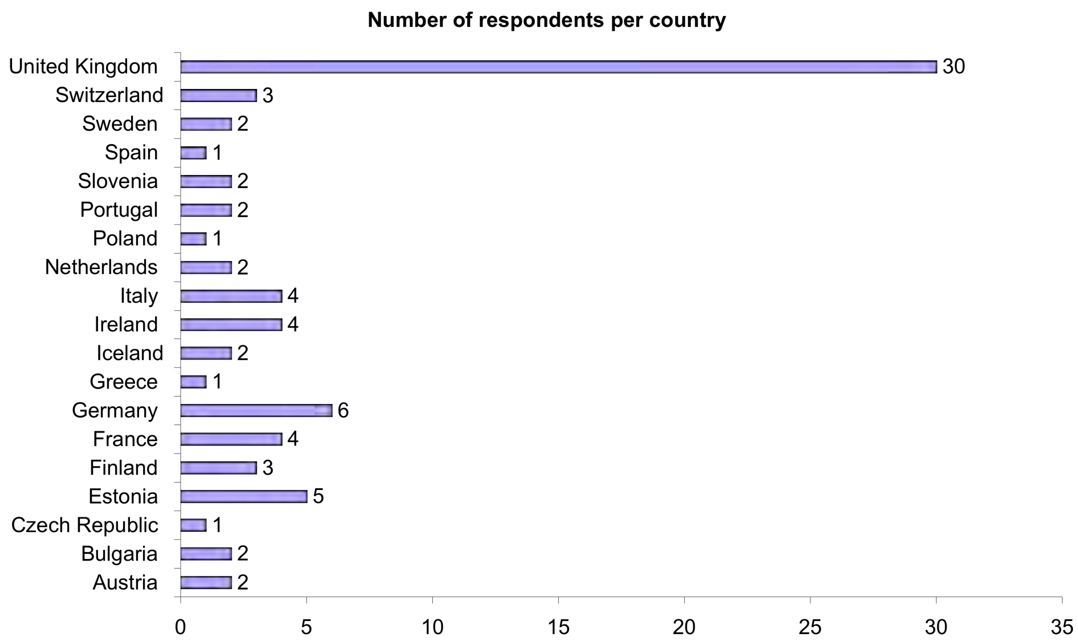


Figure 15. Number of respondents per country

4.2. Data collection practices

It was found that nearly all municipalities in the study are collecting data on building water, electricity and gas consumption. As expected, electricity consumption data is collected in most of the municipalities, 71 out of the 76 municipalities that participated in the study, followed by building water consumption data (65) and gas consumption data (62).

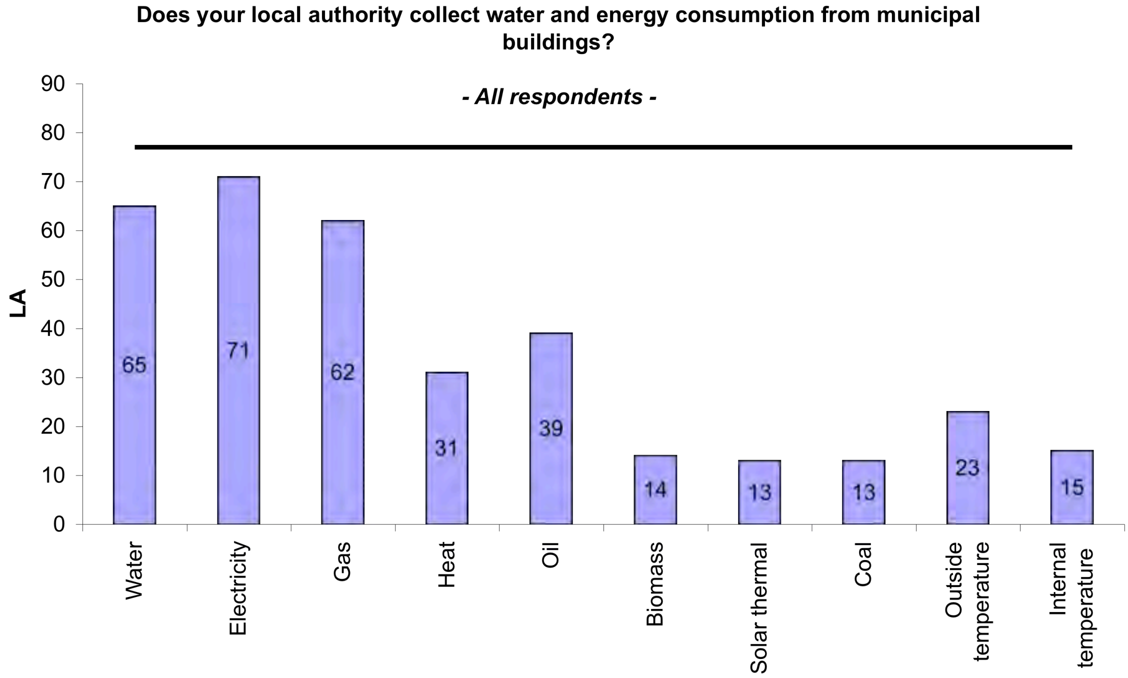


Figure 16. Water and energy data being collected in European municipal buildings

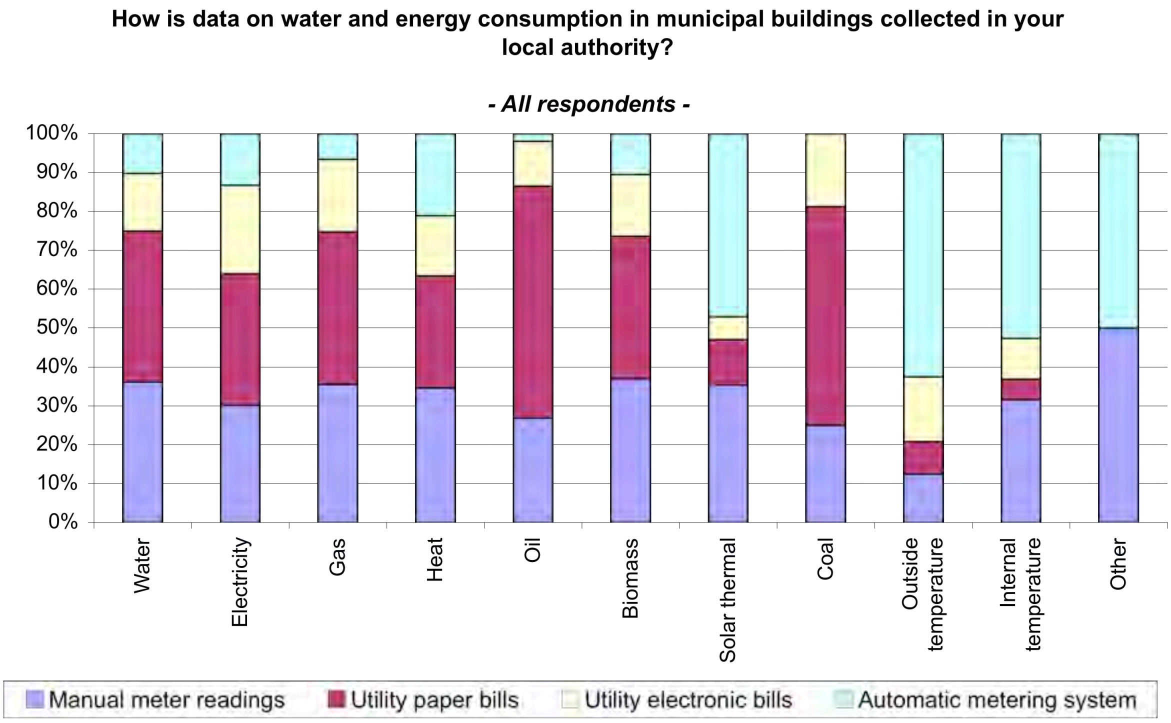


Figure 17. Type of water and energy data collection systems per building utility

A large number of local authorities collect building energy and water consumption data from manual meter readings. Utility paper bills have an important role in European municipal building water and energy management. Electronic bills provided by utilities are also source of information on water and energy use.

Automatic metering systems are still not very common for metering the most important building utilities: water, electricity and gas (10%, 13% and 7%, respectively). However, automatic systems are being used to monitor the new and renewable energy use (21% for heat and 47% for solar thermal) and also temperature data (63% for outside and 53% for inside temperature).

Concerning the frequency of water and energy data collection, more than a third of the water and energy data from municipal buildings is collected in monthly periods. Data collected in periods larger than the month (in which we included intermittently collected data) represent 41% of all data. Only about 13% of the data is collected in sub-daily periods, i.e. in half-hourly (or less) intervals.

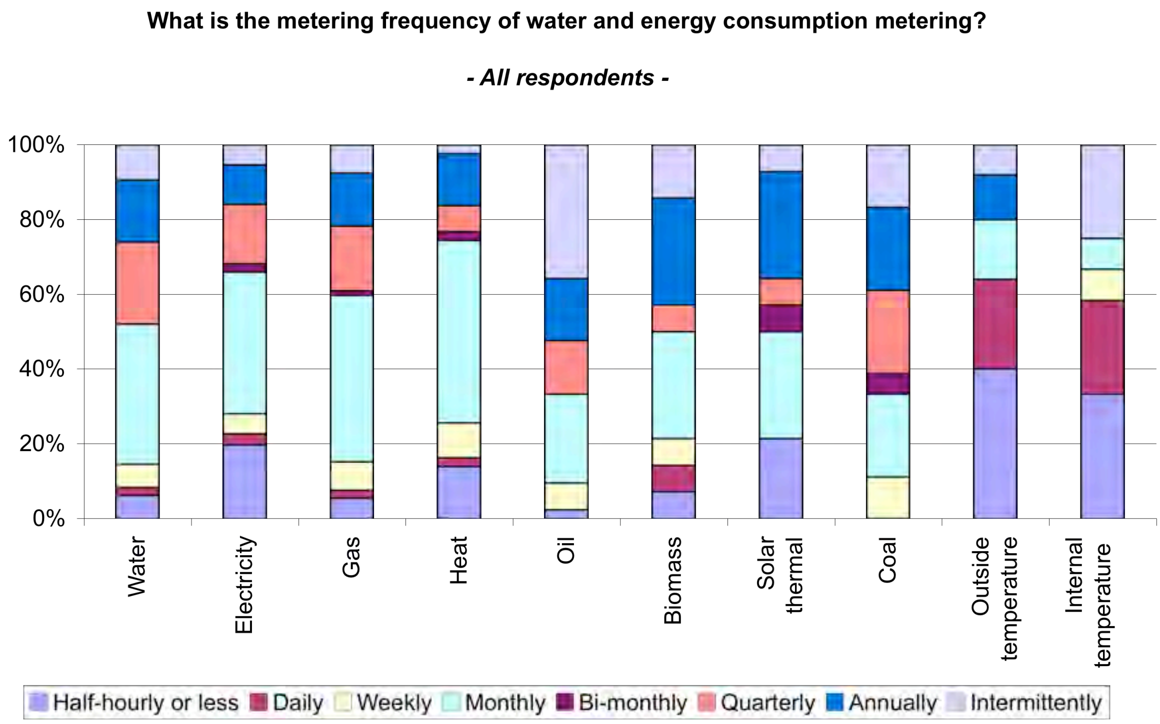


Figure 18. Frequency of water and energy data collection systems per building utility

Figure 18 shows that data collected in short time series (half-hourly or less) periods is less than 20% for water and energy utilities, except for solar thermal energy production and temperature data (inside and outside). Half-hourly electricity data collection is more frequent than half-hourly water and gas data. For the most important utilities (water, electricity and gas), monthly data collection is the most common metering frequency, however, quarterly and annually collected data are also very common.

4.3. Applications of collected data

The potential applications of collected data are quite varied. The survey allowed energy managers to select multiple answers from a set of applications and they could also include additional information and comments. A ranking of the selected applications of collected data is presented, the number of answers on each of the items is in brackets:

- To identify excessively high levels of consumption in normal use (61);
- To verify utility billing data (59)
- To monitor unusually high or low consumption to identify energy wastage (58);
- To measure and verify energy/water savings measures (55);
- To communicate with buildings occupants in order to change behaviour (51);
- To perform benchmarking analysis with similar buildings (47);
- To negotiate with utilities (e.g. in calls for tender for energy supply) (41);
- To measure municipal buildings greenhouse gas emissions (40);
- To communicate with general public, by displaying building performance (36);
- To check for faults affecting consumption permanently (35);
- To prepare dossiers for performance contracting in municipal property (23);
- To ensure that consumption is within the utility contract and avoid penalties (20);
- Not effectively used (11).

The most important application of water and energy use data is to monitor consumption, identify high levels of consumption, identify wastage, measure and verify savings. In addition water and energy data is also used to communicate and to promote behaviour change of building occupants. Benchmarking with similar building types is also an important application. The verification of billing information is another important use of water and energy data.

Additionally, respondent's comments suggested that data is also used to perform energy costs calculation and budgeting, and there were several references to calculation of indicators (carbon emissions, environmental management, DISPLAY® Campaign and NPI) and to building certification under the European Directive on energy performance in buildings.

Finally 14% (11 in 76) of the local authorities that participated in this survey responded that the water and energy data collected is “Not effectively used”. Understanding the reasons why some local authorities do not effectively use building water and energy data in their management is out of the scope of this survey. However, it is very likely that this is caused by insufficient staff resources to analyse collected water and energy data.

4.4. Energy analysis practices

Question 7 of the survey was an open question, aimed at getting more information on the analysis techniques used by energy managers. Energy managers did not refer to new or different techniques from those presented in the literature review.

The respondents stated several techniques, the most cited are listed below and the number of citations is in brackets:

- Analysis using Excel charts (9);
- DISPLAY® tool - year on year comparison, before and after energy efficiency measures (9);
- Benchmarking – from internal benchmarks for group of owned buildings, comparisons with similar building types and against national benchmarks (8);
- Analysis capacities and reports generated by commercially available software packages - such as STARK, TEAM, ECS, Erbis, Systems Link, Declic, Energy Monitoring & Controlling Solution, Signum and Enercompta (7);
- Graphs showing energy profiles against time (6) - example: Half hourly data for analysis of use profiles for the larger electricity supplies;
- NPI - a wide range of indicators was cited, from EMAS indicators to CO_2 emissions calculations, and the conventional consumption per unit floor area consumption against local benchmark, MWh/m^3 in month/year (6);
- Regression Analysis with degree days and CUSUM (event detection technique used in energy monitoring and targeting) (5);
- Simple year on year, trend analysis and historical comparisons (5).

Energy managers use benchmarks (published and internal to the local authority), based on NPI, mostly on an annual basis. Simple visualisation techniques, comparisons between past and current consumption, mostly on a monthly basis, are also used. There were a few references to M&T techniques (degree-days and CUSUM). There is only one reference made to the use of half hourly electricity data in the analysis, and this concerned the use of profiles. There are specific references to proprietary software packages. Microsoft Excel is also used in several local authorities, and it was referred to in 9 cases. The DISPLAY® tool was also referred to by 9 respondents.

Question 8, asked the respondents to select from a list of commonly used energy analysis techniques. The results are presented in the Figure below.

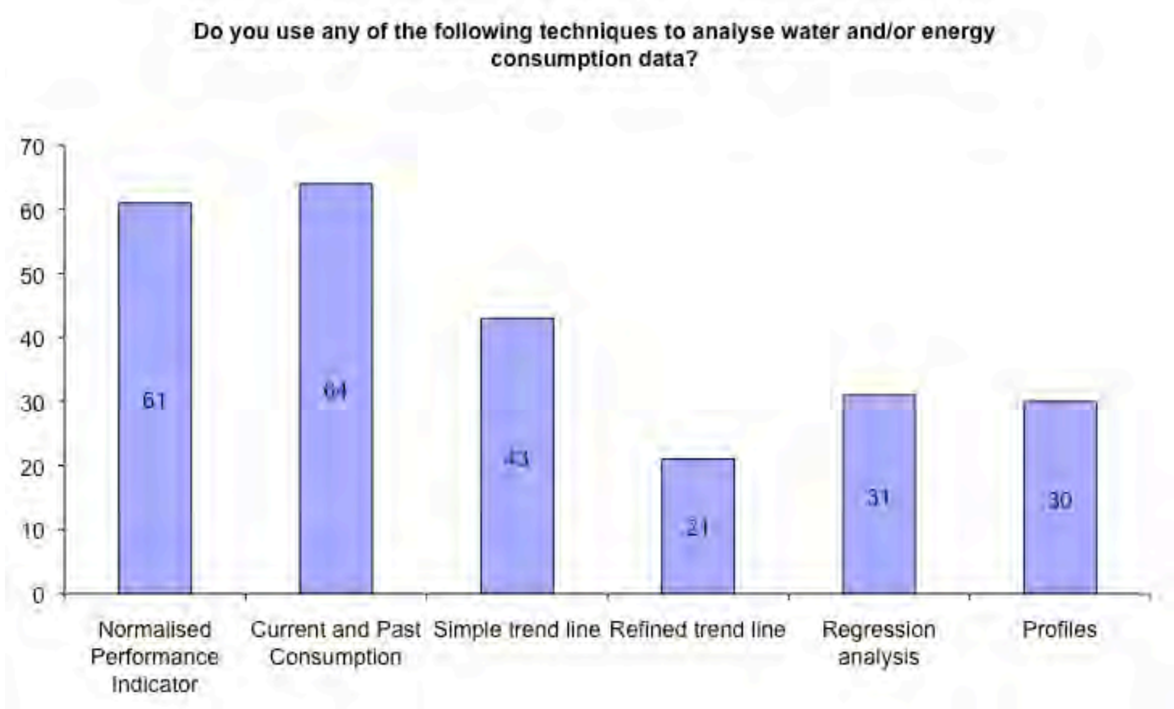


Figure 19. Energy analysis techniques used to analyse water and energy data

The current and past consumption and NPI are the most used techniques, followed by the simple trend line (energy against time). Regression analysis, profiles, and refined trend line are used in less that half of the respondent local authorities.

Most local authorities use a standard rating system or benchmark to assess their building's performance. Of the 19 European countries represented in the survey 11 have a national standard rating or published benchmarking system that can be applied to assess performance in municipal buildings, these countries are: Germany, United Kingdom, Netherlands, Czech Republic, France, Austria, Bulgaria, Sweden, Switzerland, Finland and Estonia.

The survey showed that 54%, (41 out of 76) local authorities, use a software tool for analysing the collected building water and energy consumption.

4.5. Characterisation of European energy managers needs

The final open question aimed at acquiring information about the needs and expectations of the people in charge of metering and monitoring water and energy consumption in municipal buildings in Europe.

Concerning metering systems the main requirements were the following:

- Automatic metering, constant monitoring and real time data;
- Accurate data (not estimated);
- Data management and secure databases;
- System with flexible data import facilities: manual, invoice, electronic data from utilities and automatic metering.

Concerning the water and energy data analysis, including analysis techniques, the requirements were the following:

- Normalised Performance Indicators
- Building classification according to the EPBD;
- Benchmarking for costs, energy, water and carbon emissions (local and standard);
- Historical comparisons, current and past consumption;
- Weather adjustment and building energy signature (energy against outside temperature or degree days);
- Constant and weather dependant targets;
- Exceptions reports, targeting, alarm, warnings, tolerance alarm / error report;
- Tariff analysis and billing verification;
- Budget forecasting;
- Visualisation of data.

There were some additional features for monitoring systems that were indicated:

- More automated analysis;
- Easy to use software with user-friendly interface.

The main reporting features suggested were the following:

- Suitable report templates and custom reporting;
- Report in units that people understand (money, amount of light bulbs, etc.)

4.6. Conclusions

This was the first comprehensive survey of municipal energy mangers, focused on the collection and analysis of data. It provided information about data collected, tools, analysis techniques used, difficulties and real needs.

The key findings were that:

- Data is being collected typically in monthly periods from paper bills and manual meter readings, but it is being inserted in computer databases and about 54% of the respondents use some kind of software tool to analyse data;
- Short time series data, in hourly or sub-hourly periods is not yet very frequently used, only about 13% of the municipalities in the study are using technology that enable the collection of this time of building energy consumption data. However, the trend is for an increase in the availability of sub-hourly data, and energy managers are calling for near to 'real time' data;
- The most important applications of monitoring systems are: identification of high levels of consumption and wastage and measurement and verification of savings measures, verification of utility billing data and benchmarking with similar building types. Water and energy data is also used to communicate and to promote behaviour change of building occupants;
- Techniques used by energy managers (including the ones featured in commercial software packages) are not sophisticated enough for dealing with large volumes of data. Energy managers use annual benchmarks (PI and NPI), and simple visualisation techniques, including past and present analysis on a monthly basis. There are a few references to the use of M&T techniques;
- Energy managers need an easy to use, straightforward, and as much as possible automatic software tool to analyse building energy data. These tools need to comply and support the implementation of new legislation and regulations, such as EPBD and ESD.

Very little research has been carried out to address energy managers' needs, and on the improvement of energy analysis techniques and software tools currently in use. From the survey it was found that energy managers are supportive of the deployment of smart metering technology. It was also found that energy managers are calling for automated tools for the analysis and interpretation of metered energy data. Therefore, new benchmarks using sub-hourly energy and water data could benefit municipal energy managers by providing more effective building energy performance assessment and automating the identification of potential saving opportunities.

The following chapter presents the source of the primary energy meter short time series data collection used to validate the thesis. The new approach to the analysis of primary energy meter short time series data using quantitative indicators for the characterisation of the load demand profile shape and the building energy signature is proposed in the subsequent chapter 6.

Chapter 5. Metered data collection and analysis

The exploratory survey presented in the previous chapter provided information about the metering and monitoring practices in local authorities in Europe. It was found that data is collected manually, typically on a monthly basis, but quarterly and annual periods are also frequent. Very few energy managers have access to automatic metering systems, and they employ conventional building energy analysis techniques, even when software tools are accessible.

A best practice example of municipal energy management in Europe is the metering and monitoring system installed in Leicester City Council buildings. This is a fully automated metering system that collects electricity, gas and water data in half-hourly intervals. This aM&T system responds to some of the practitioners' needs expressed in the survey. However, this automatic metering system has some limitations, particularly concerning the analysis and interpretation of data. The detection of savings is manual, and is related to a great extent to the energy managers' experience.

Leicester energy management team has the responsibility to analyse data generated by the aM&T system and provide feedback to building managers, whom are required to take corrective actions to avoid energy wastage in Leicester City Council buildings.

The data collected by Leicester energy management team was made available for the current study. This data was primary metered electricity and gas half-hourly data from municipal buildings in Leicester, half-hourly outside temperature data for one location in Leicester city centre and floor area for several buildings.

This chapter starts by providing a description of the main technical specifications and operation conditions of the Leicester's energy and water metering system. This is followed by a description of current work procedures for data management, error detection, re-sampling of missing data and time series data analysis using Matlab® software. This chapter also describes the evaluation of available datasets, and the selection criteria of metering data suitable for analysis. It also includes a conventional energy performance assessment of selected buildings using NPI and benchmarking exercise using Carbon Trust reference values.

The chapter concludes with a discussion of the precautions taken with data handling and management, limitations of available data, and recommendation for further research on data management.

5.1. Leicester City Council metering system

Leicester Energy Agency is currently collecting utility data from around 300 premises, mostly owned by Leicester City Council. Typically the data collected is total electricity, gas and water consumption directly from the primary meter. Sub-metering data is also available for several sites. The data collection frequency is usually 30 minutes. Half-hourly outside temperature is also being collected from a site in Leicester city centre.

Half-hourly energy and outside temperature data are collected using a proprietary system, which combines hardware for metering the utilities, and a software package for processing data. This is what in the UK is commercially called Automatic Monitoring and Targeting system, or simply aM&T. Leicester Energy Agency installed DATA BIRD and DYNAMAT, respectively, an AMR system based on low-power radio technology transmitters, and a data analysis software package. These products are available from Energy Metering Technologies, Ltd.

Leicester Energy Agency's energy management team started the installation of this aM&T system in early 2001, with a pilot project of just 10 buildings. Over the years the system expanded to include more municipal buildings, but also local businesses. All the data collected from the start of the installation of the aM&T system until September 2006 was available in the database supplied to researchers at IESD.

5.1.1. Electricity and gas metering in Leicester City Council buildings

The DATA BIRD automatic data collection system installed in Leicester is described in the Energy Efficiency Best Practice Programme - General Information Leaflet 49 (DETR, 1996). Figure 20 presents the typical configuration of the metering system: the electricity, gas and water meters (M), local data logger (DBT1, 2, 3 or 4), central receivers (DATA BIRD) and the central computer where the data is stored and analysed. The DATA BIRD system monitors energy and water consumption in Leicester City Council buildings, and was described previously (Ferreira, 2002; Ferreira, et al., 2003; Webber, et al., 2007). An overview of its cost-effectiveness was presented in (Ferreira, et al., 2007) and a detailed technical presentation is available from (Brown & Wright,2008).

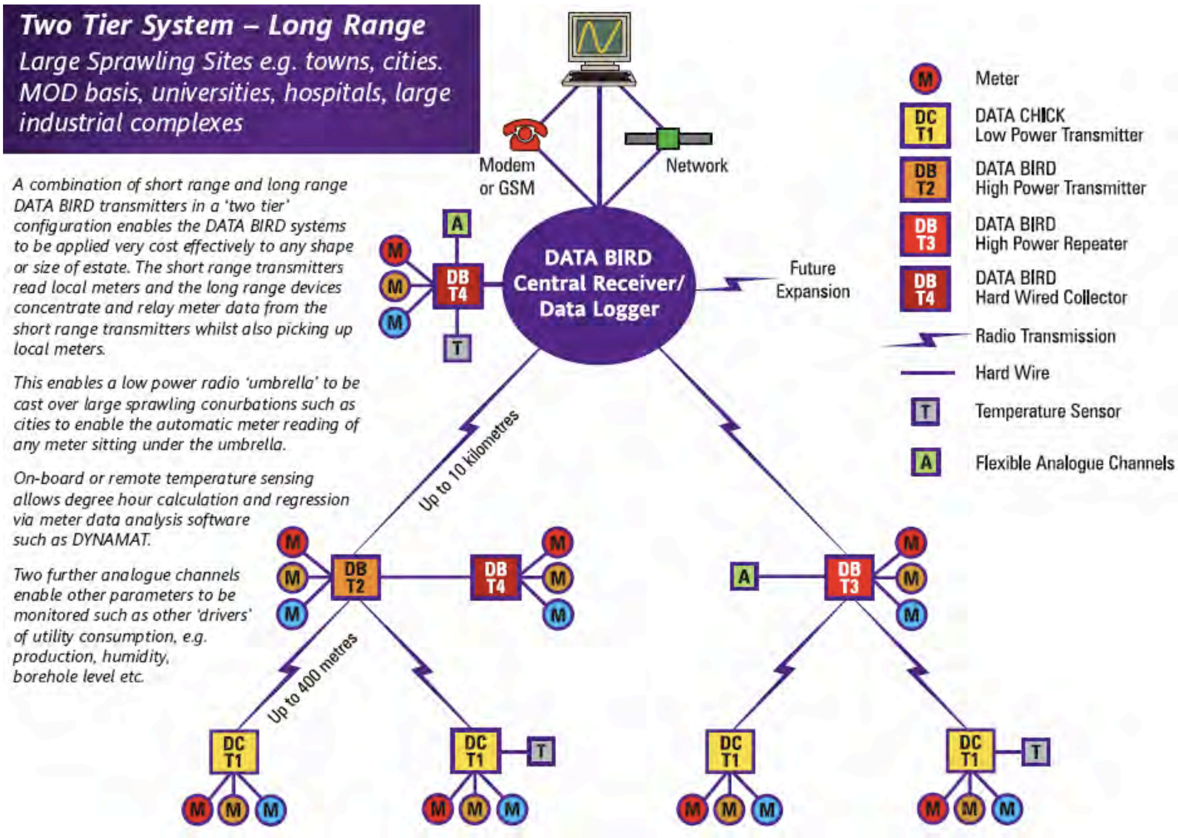


Figure 20. Elements of Leicester's metering system (in DYNAMAT brochure)

The main advantage of the DATA BIRD system is the use of licence free low-power radio communication of data from the data loggers located inside the building to one of the seven central receivers distributed within the city, Figure 21. Data transmission is completed at zero cost from the building to the central receivers. Data from buildings within an area of the city is concentrated on the central receiver, and is transferred every day, by modem/landline, to the central computer.

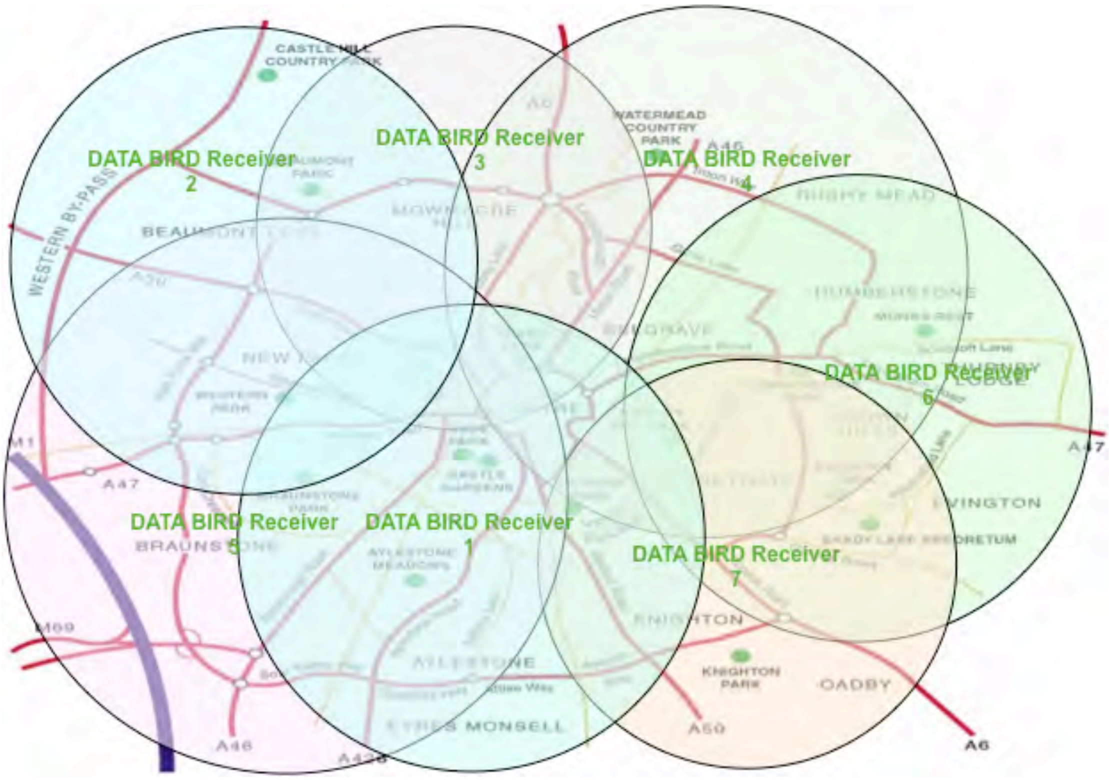


Figure 21. Coverage of the seven DATA BIRD radio central receivers over Leicester

The typical arrangement in each building is a configuration based on a logging system, which comprises meter pulse detectors, data loggers, radio transmitters and a radio antenna, Figure 22. Each day, at a fixed schedule, the readings from each meter stored in the local data logger, are transmitted by low power radio to one of seven main receivers. The receivers then forward the data on to a central computer located in Leicester Energy Agency. The DYNAMAT data analysis software is installed on this central computer for processing, managing and analysing data.

Most of the data collected by Leicester's DATA BIRD metering system is derived from (electricity, gas and water) meter pulse outputs. These outputs are electric pulses produced by most metering equipment. Pulse outputs convert the analogue value to electric pulses, which can then be converted into digital units of absolute consumption. The pulses are transmitted from the meter to the local data-logger. The pulse outputs are binary signals. For example, 5 pulses are converted into 1 Wh of electricity use, or 10000 pulses are converted into 1 m^3 of gas consumption. The conversion of pulse outputs can be done in the local data logger. The use of pulse outputs is a common protocol that is available from all types of meters, from all manufacturers. Therefore, data collection and communication is harmonised.

Other aM&T systems have specific protocols for dedicated meter reading given the meter actual reading (the meter cumulative face reading), for example the M-Bus protocol, but these are more costly, because new meters have to be installed.

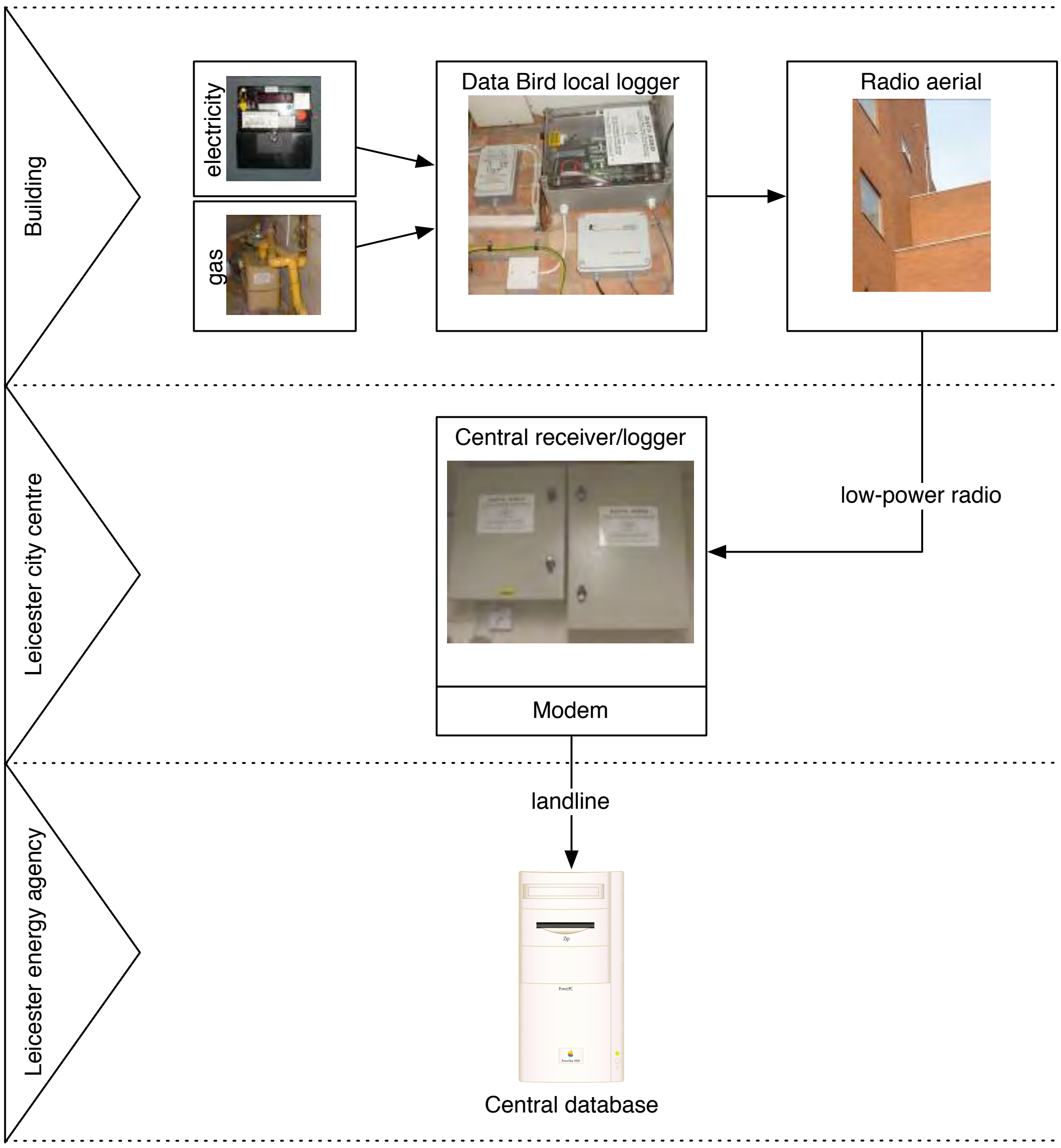


Figure 22. Elements of Leicester's energy metering system

5.1.2. Outside temperature data and floor area data

Additionally, the aM&T system acquires external temperature data from one temperature sensor located in St. Peters, Highfields in Leicester city centre. The location and positioning of a temperature sensor affects the quality of the collected data. It would be important to have several sensors installed at different locations in Leicester in order to have some improved inference and quality in the results. Ideally there should be an external temperature sensor installed in each monitored building. However, the data available is derived from that sensor in St. Peters. In this research project it was decided to use this data, mainly because the analysis include exclusively Leicester buildings located around the city centre. The use of this temperature data allowed working with the same data resources of Leicester energy management team. This served the purpose: to develop, test and validate an innovative approach to the analysis of short time series energy and outside temperature data.

Future research, which may include Leicester building and buildings in other locations, should start by assessing of St. Peters temperature data, and other outside temperature data sources for Leicester, in particular the newly installed DMU weather station, which temperature data can be used in future research projects.

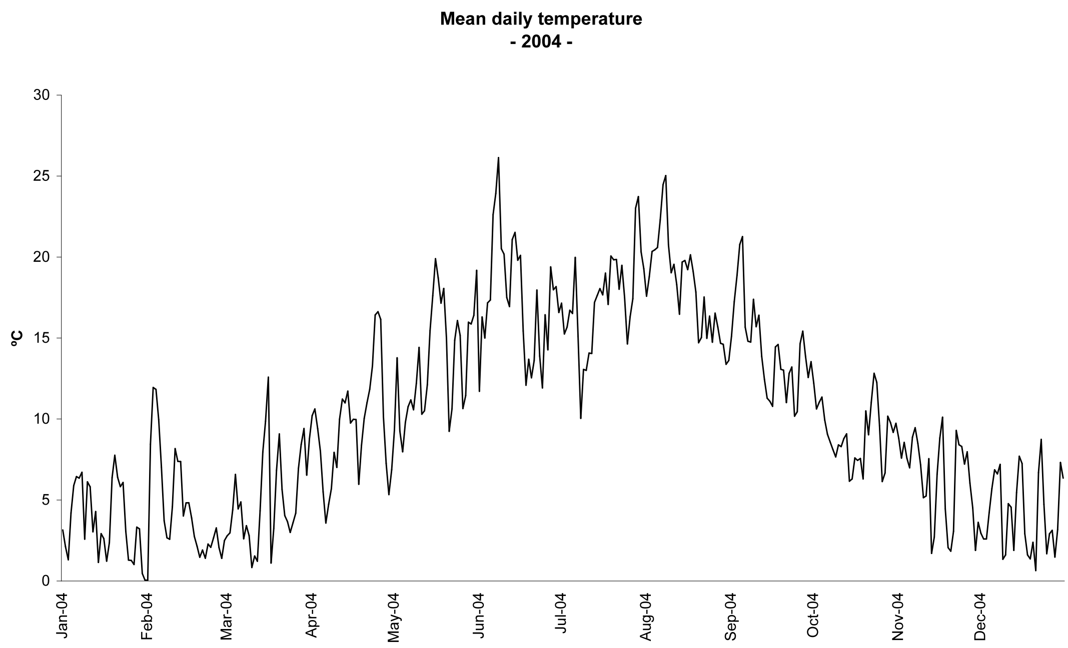


Figure 23. St. Peters daily mean outside temperature data for 2004

Floor area data was also available for Leicester City Council buildings. Floor area data supplied by Leicester Energy Agency is the Gross Internal Area (GIA).

GIA is total building floor area measured inside external walls. The GIA data for several buildings was determined by recent surveys conducted to collect the required information for the calculation of Leicester City Council buildings DEC – Display Energy Certificates.

5.2. Data storage and management

The metered data is stored in a software database. DYNAMAT software processes the raw data, corrects any existing data errors and eliminates missing data. The data is then ready for the analysis conducted by the energy manager. The software includes visual display of data (including profiling), regression analysis with degree-days, cumulative sum of the differences from an existing pattern of consumption, year on year comparison and reporting functions, including exception reporting. A complete overview of the analytical capabilities of DYNAMAT is available in (Ferreira, 2002).

The data-cleaning algorithm applied by DYNAMAT is not known. In order to avoid introducing unspecified bias in metered data, it was decided to use the raw data stored in the database, before any handling or cleaning processing from the DYNAMAT software. This database was retrieved in October 2006, and has an approximate data volume of 3 gigabytes, and includes about 52 million half-hourly data points.

The amount of data handled requires a powerful database with Standard Query Language (SQL) capability or Oracle databases. For this research project, a SQL database was selected. The database supplied by Leicester Energy Agency in text format, was converted and stored in a Microsoft® SQL Server™ 2005 database. SQL Server is quite user friendly and incorporates some basic data analysis functions. However, databases were not able to produce the advanced visualisation plots described in previous chapters. So, it was sought the integration with other software packages with more advanced visual analysis capabilities. In the current study the Microsoft® SQL Server™ 2005 database was connected with Matlab® software, from Mathworks, which was used to re-sample data and to conduct data analysis through the use of visualisation techniques (line plots, 3D and 2D) and numerical short time series performance indicators (load demand shape profiles and regression coefficients).

The following diagram presents the main data flows and data management functions. A detailed presentation of the algorithm used in offered in the Appendix B.

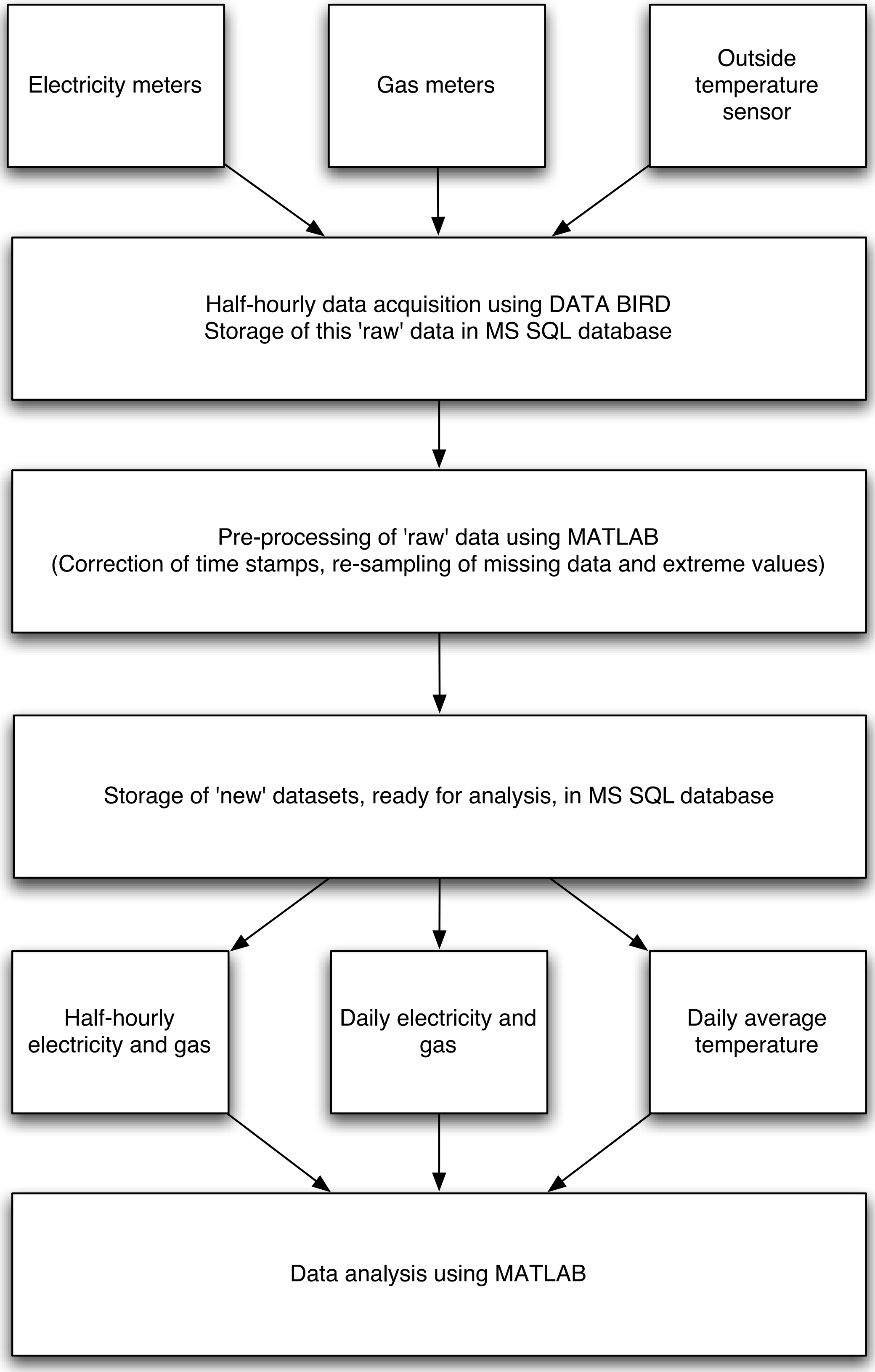


Figure 24. Schematic presenting data flows and data management functions

The diagram in Figure 24 presents an overview of the data flow, from the data acquisition from the meters and temperature sensor using DATA BIRD to the storage of data on a MS SQL server database. This database computed and stored the input variables used in the data analysis:

- Half-hourly electricity consumption
- Half-hourly gas consumption
- Daily gas consumption
- Daily electricity consumption
- Daily mean temperature

These variables are the inputs to the visualisation and performance indicators calculation tool that was implemented in Matlab®. However, before the data was stored in the MS SQL database, it had to be pre-processed. Data pre-processing consisted mainly in the correction of data stamps, re-sampling of missing data and elimination of outliers.

5.3. Data cleaning and pre-processing raw data

The DATA BIRD can be considered to be robust data communication system. However it introduces different types of errors in the data collected. These are typical reading errors associated with remote data communication. There are several approaches to correct these errors. Periods of missing data can be interpolated using mean values of known energy consumption, linear interpolation, cubic splines and Fourier series. However, there is no unique or standard method for data correction. Modern smart metering systems introduce few errors than DATA BIRD, mainly because they have two-way communication systems that allow data checks and data recovery.

Brown and Wright (2008) offer an algorithm to clean data errors found in Leicester City Council database. This algorithm is based on the fact that the most common error is the occurrence of 'spikes' from communication dropouts. A dropout occurs when a meter pulse is being sent by radio, but for some reason the communication is interrupted. This causes the delay of the signal to the other half-hour. This last data point includes not one but two (or more) pulse outputs, and when integrated it looks like a 'spike', i.e. a higher than expected data point. Brown and Wright (2008) suggest an automated way to eliminate these data. They used an automatic detection of the spikes based on the first differential of sample rate, and then correct the error by re-sampling data using cubic splines. Other alternatives consist in the use of linear interpolation and Fourier series.

Baltazar and Claridge (2002, 2006) compared the application of these three methods (linear, cubic-spline fits and Fourier series interpolation) for hourly electricity data for restoring short term missing data in time series of building energy use and weather hourly data. They concluded that linear interpolation is a better approach for filling gaps from one to three hours long. They also found that linear interpolation is superior to the cubic spline and Fourier series methodologies for filling gaps of dry bulb and dew point temperature time series data, using the mean bias error as selection criteria. However, for hourly building energy data, the most suitable approach is the use of Fourier series with at least 24 data points before and after each gap.

In the available data, most of the errors are consistent with 'spikes', where the total energy consumption in the period of blank data before the 'spike' is known. The procedure described in (Baltazar & Claridge,2006) is for when the total consumption in the period of missing data is not known. Apparently, Brown and Wright (2008) applied their method in the same way. However, there is another alternative, a simple method for correcting data when total energy consumption is known.

The Portuguese energy services regulator published a standardised approach to correct common errors found in electricity remote metering quarter-hourly data used for utility billing (ERSE, 2003). They suggest the use of the mean energy consumption for re-sampling data in each integration interval (in our case the half-hour) when the total energy consumption in the interval of missing data is known.

An automatic error correction algorithm was applied to the entire database using Matlab®. The simple algorithm performs the following routines:

1. Detection of the missing data period;
2. Identify the number of half-hourly intervals of missing data;
3. Identify the value of the 'spike' in the first reading after the missing (blank) data period;
4. Divide the 'spike' value, i.e. total energy consumption in the missing data interval, by the number of intervals;
5. Re-sample missing data with the mean half-hourly energy consumption

The following table presents an example of the application of the automatic data re-sampling method used in the current work.

Table 4. Data re-sampling algorithm

Operation	Sample of array
Error detection: data missing for 3 half-hourly intervals	1 2 2 3 3 **null null null 12** 5 4
Re-sampling of data: 12 kWh divided by 4 intervals	1 2 2 3 3 **3 3 3 3** 5 4

When the energy consumption in the period of missing data was not known, the data was re-sampled using linear interpolation. After running the data re-sampling algorithm, data was inspected visually using 2D and 3D plots. This was done manually, meter by meter, in order to select the datasets suitable for analysis. The visual inspection intended to detect data problems in pre-processed data; to select good quality metered data and relevant buildings further analysis.

5.4. Buildings selection

Half-hourly data considered viable for analysis comprises a wide range of non-domestic buildings and premises: offices, schools, libraries, leisure centres, administration offices, elderly persons homes, warden assisted accommodation, etc.

The buildings selected have electricity and gas primary meters, and a complete dataset for the year 2004. These conditions were fulfilled for 162 primary meters channels, corresponding to 81 municipal buildings selected for analysis.

The first building selection criterion was the exclusion of meter channels (and consequently buildings) with incomplete datasets for the year 2004, considered to be the reference year for the analysis. The year 2004 was selected to be reference year mainly because this was the period when a significant number of buildings had metering equipment installed. However, in this period the municipal energy managers had implemented few corrective interventions. Therefore, by using 2004 data it would be expected to identify diverse energy saving opportunities.

A second criterion was the selection of only main, or primary, electricity and gas meters. These meters should register total energy use, the variable of interest in the current study. Some buildings have very complex metering arrangements, and include different levels of sub-metering and other unusual meter configurations, with virtual meters and no main meters. For the current study only primary meters electricity and gas data were considered, i.e. total energy consumption. This allows comparison between premises/buildings that are similar in type and use.

The last criterion consisted in the selection of municipal buildings exclusively. Most of the buildings had been previously classified for CaRB project (Brown and Wright, 2008), and this information was made available for the current research project. Meter channels from local businesses, workshops, indoor and outdoor markets, depots, bus stations, and other non-classified buildings were excluded.

The classification used in the CaRB project and also adopted for the current work is the Pclass codes presented in (Bruhns, et al., 2000). The Pclass codes is a classification based on the activities conducted in the of non-domestic buildings premises. There are four main categories of Pclass codes: Commercial, *Hospitality* (buildings open to the public ranging from hotels, libraries, museums and leisure centres), Industrial and Social buildings; these correspond to codes starting with letter C, H, I and S, respectively. The code is usually composed of a second letter, for example CO is the classification of commercial and public offices. The database consisted mainly of commercial and public offices (CO), hospitality buildings devoted to leisure (HL), schools (SE) and social community buildings (SQ). HL buildings were divided in libraries and museums (HL1) and sport centres with and without swimming pool (HL3). Similarly for SQ buildings, a division between community centres (SQ10) and hostels and care homes (SQ21) was introduced. Table 5 presents the Pclass codes used to classify selected buildings from Leicester half-hourly utility metering database.

Table 5. Classification and distribution of building types

Building type (Pclass)	Number of buildings	Number of datasets	Activity classification
CO	19	38	All type of commercial, local and central government office activities
HL1	9	18	Museums, art galleries or libraries
HL3	5	10	Leisure centres, sports halls, swimming pools, etc.
SE	11	22	All type of schools, from kindergartens to universities
SQ10	8	16	Community centres, neighbourhood centres or social clubs
SQ21	29	58	Social hostels, children homes, elderly people homes, warden assisted accommodation

The following figure presents a summary of the electricity consumption against floor area. This was done for the baseline year – 2004. Note that floor area was available for about 64 of the 81 selected buildings. Figure 26 presents the gas consumption per floor area for the same buildings.

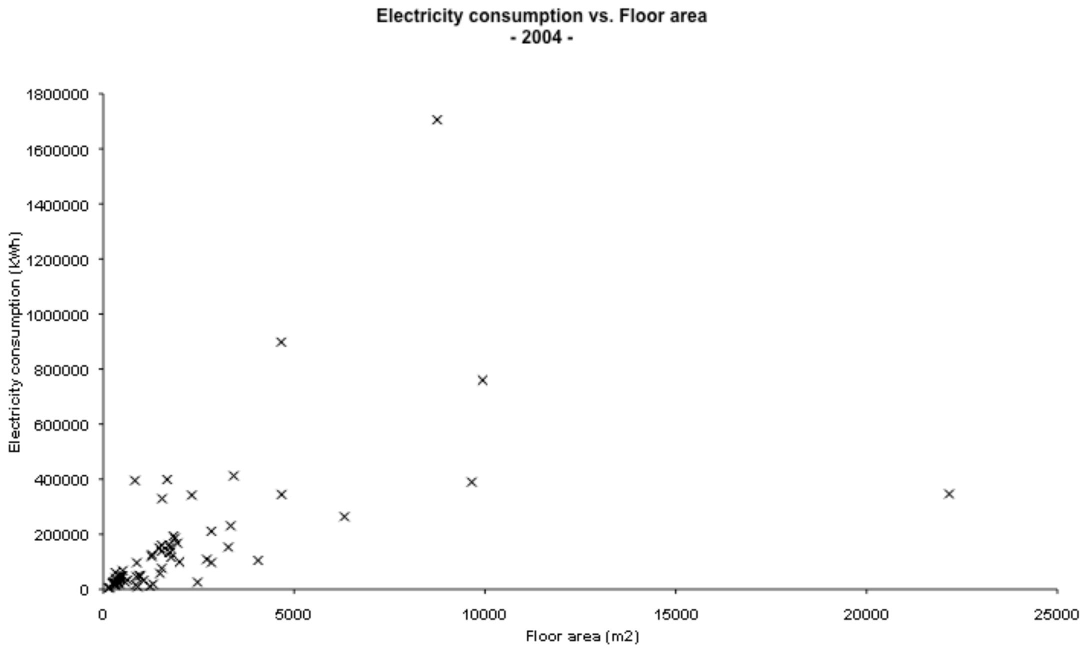


Figure 25. Electricity use per square metre

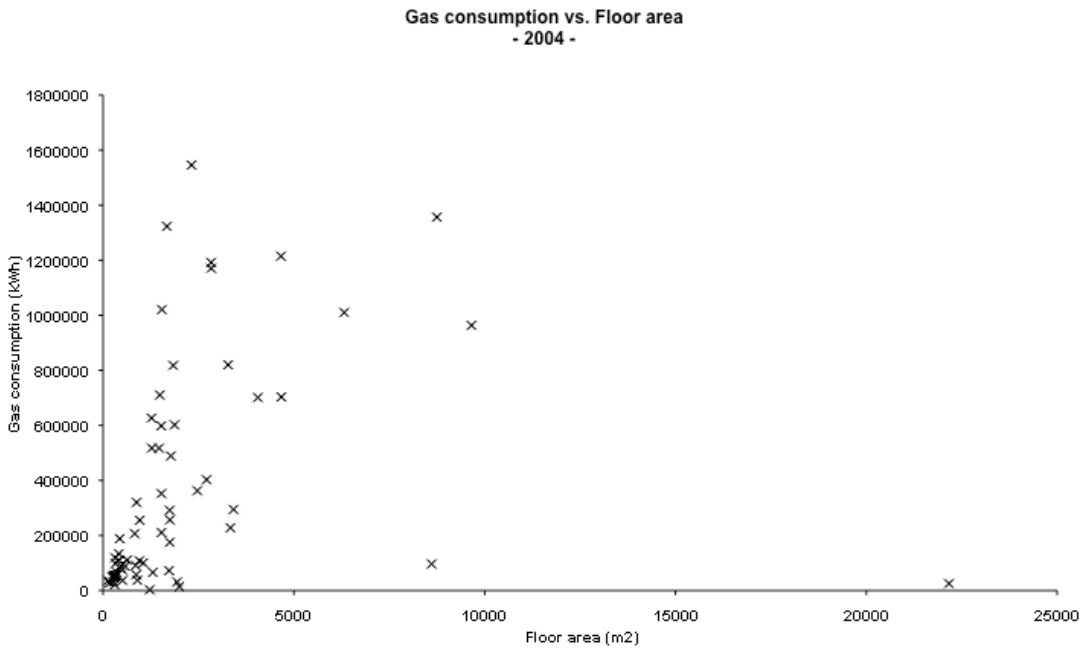


Figure 26. Gas use per square metre

Most of the buildings are below 5000 m^2. The smallest building is 136 m^2 (Aylestone Library) and the largest building is 22166 m^2 (New College). In fact New College is not just one building. The metered energy (electricity and gas) consumption is for the total New College premises. Moreover, metered data refers to energy consumption of premises and not individual buildings. Premises can be part of a building, an individual building or several buildings, which in this case is owned or leased by Leicester City Council. However, the author assumed the freedom of using the word 'building' instead of 'premise', because this is true for most of the 81 premises selected.

5.5. Energy performance of selected buildings

Annual normalised performance indicators (NPI) were produced in order to assess the overall energy performance of selected buildings using a conventional approach used by energy managers. NPI results are compared with the method developed under the current work in the discussion presented in chapter 10.

As presented in Chapter 2, annual performance indicators are offered in several guidance publications and books, as a method to benchmark buildings energy performance. The survey to European municipal energy managers also found that indicators and benchmarking is one the most common energy analysis techniques used by them. In the UK the Carbon Trust published the Energy Consumption Guide on Energy use in Local Authority Buildings (Carbon Trust, 2004), which suggests the use of annual NPI to assess building energy performance. It includes a list of typical results in units of kWh/m^2 per annum, separately for electricity and fossil fuels for several types of municipal buildings. The next table presents the NPI for the buildings included in the current study.

Table 6. Energy performance benchmarks per building type (typical NPI values)

Building type (Pclass)	Additional characteristics	Electricity NPI ($kWh/m^2/year$)	Gas NPI ($kWh/m^2/year$)
CO	naturally ventilated	81	143
CO	air conditioned	203	160
CO	town hall	111	205
HL1	library	46	210
HL1	museum	70	142
HL3	dry sports hall	105	343
HL3	swimming pool	258	1321
SE	-	34	157
SQ10	-	33	187
SQ21	-	68	432

The electricity NPI is calculated using the annual electricity consumption divided by the Gross Internal Area (GIA), as in Equation 3. However the gas NPI is slightly more complicated to calculate. It includes a degree-day correction coefficient and requires the breakdown between weather and non-weather gas use. This breakdown was done using the non-weather related energy consumption determined, the *c* coefficient that results from the application of a regression inverse model described in detail in Chapter 6. The degree-day corrected factor was calculated by dividing the total annual degree-days for 2004 (2,196) by the standard degree-day (2,462) included in the Carbon Trust guide.

$$NPI_{electricity} = \frac{E_{electricity}}{GIA}$$

Equation 3. Electricity NPI calculation

$$NPI_{gas} = \frac{E_{gas} \times DD_{factor} + c}{GIA}$$

Equation 4. Gas NPI calculation

The calculation of NPI was limited to the number of buildings with floor area data. The number of buildings for which it was possible to break down between weather and non-weather gas use also limited the calculation of gas NPI. Overall it was possible to calculate 64 electricity consumption NPI and 55 gas consumption NPI. Using the Carbon Trust benchmarks it was possible to identify buildings with unusually high NPI, which could be indicative that energy wastage is occurring, or in other words, buildings with untapped energy saving opportunities.

The electricity NPI are presented in Table 7. According to this indicator it is possible to say that about 36 out of 64 of Leicester City Council buildings are using too much electricity.

The gas NPI are presented in Table 8. About 26 out of 55 buildings were considered to have high gas consumption according to NPI calculations and published benchmarks.

Table 7. Electricity NPI results

Meters	Building type	Actual NPI (kWh/m2)	Typical NPI (kWh/m2)	Actual % of Typical
16 New Walk Elec	CO	69	81	85%
308 Melton Rd Elec	CO	n/a	81	n/a
31 Lower Hastings St Elec	SQ21	55	68	81%
33 Lower Hastings St Elec	SQ21	191	68	281%
38 Upper Titchbourne Elec	SQ21	44	68	65%
47 New Walk Elec	CO	84	81	104%
Abbey House EPH Elec	SQ21	98	68	144%
Arbor House EPH Elec	SQ21	99	68	145%
Ash Field School Elec	SE	47	34	137%
Attenborough House Elec	CO	76	81	94%
Aylestone Les Main Elec kWh	HL3	193	105	183%
Aylestone Library Elec	HL1	32	46	70%
Barnes Heath House Elec	SQ21	110	68	161%
Barnett Janner WAA Elec	SQ21	n/a	68	n/a
Beatty Ave B Elec	SQ21	n/a	68	n/a
Beaumanor Hostel Elec	SQ21	49	68	72%
Belgrave Library Elec	HL1	81	46	175%
Belgrave Neigh. Cent Elec	SQ10	105	33	317%
Bowder House WAA Elec	SQ21	n/a	68	n/a
Braunstone Oak NC Elec	SQ10	53	33	162%
Bridges House WAA Elec	SQ21	n/a	68	n/a
Butterwick Elec	SQ21	39	68	57%
Catherine Jnr School Elec	SE	50	34	148%
Central Library Elec kWh	HL1	93	46	208%
Charnwood AHO Main Elec	CO	46	81	57%
Coleman Neigh Cent Elec	SQ10	62	33	189%
Coss Fam Centre Elec	SQ10	9	33	27%
Coss Pool Elec kWh	HL3	238	258	92%
Cromwell House WAA Elec	SQ21	n/a	68	n/a
Dudley House WAA Elec	SQ21	n/a	68	n/a
Elizabeth House EPH Elec	SQ21	91	68	133%
Energy Office Elec	CO	95	81	117%
Evington Library Elec	HL1	10	46	22%
Fred.Thorpe WAA Elec	SQ21	n/a	68	n/a
Gumbrill House WAA Elec	SQ21	n/a	68	n/a
Heatherbrook Sch Elec	SE	50	34	146%
Helena Roberts WAA Elec	SQ21	n/a	68	n/a
Herrick Lodge EPH Elec	SQ21	77	68	113%
Home Farm AHO Main Elec	CO	78	81	96%
Home Improvement Agy Elec	CO	10	81	12%
Humberstone AHO Main Elec	CO	48	81	59%
Jackson House WAA Elec	SQ21	n/a	68	n/a
Judgemeadow CC Elec kWh	SE	40	34	119%
Lansdowne Neigh Cent Elec	SQ10	14	33	44%
Lansdowne Pre School Elec	SE	19	34	55%
Lough Rd Hostel Elec	SQ21	n/a	68	n/a
Marlborough House Elec kWh	CO	86	203	43%
Millgate Centre Elec kWh	SE	74	34	219%
Nether Hall School Elec	SE	n/a	34.00	n/a
Netherhall Childrens Elec	SQ21	87	68	127%
Netherhall Neigh Cent Elec	SQ10	47	33	143%
New College Main Elec kWh	SE	16	34	46%
New Parks AHO Elec	CO	107	81	132%
New Parks Les Main Elec kWh	HL3	147	105	140%
New Walk B Block Elec kWh	CO	195	203	96%
New Walk Museum Elec kWh	HL1	74	70	105%
Norfolk House WAA Elec	SQ21	n/a	68	n/a
Nuffield House EPH Elec	SQ21	94	68	138%
Phoenix House Elec kWh	CO	86	203	43%
Pollard House WAA Elec	SQ21	n/a	68	n/a
Preston Lodge EPH Elec	SQ21	105	68	155%
Reference Library Elec	HL1	76	46	168%
Rowsley St AHO Elec	CO	38	81	47%
Rupert Hse WAA Elec	SQ21	n/a	68	n/a
Saffron AHO Elec	CO	53	81	66%
Scraptoft Valley Prim. Elec	SE	40	34	118%
Southfields Library Elec	HL1	108	46	238%
Spence St Hall Main Elec	HL3	n/a	46	n/a
Spence St Pool Elec kWh	HL3	214	258	83%
St Marks AHO Main Elec	CO	72	81	89%
St Saviours NC Elec	SQ10	133	33	404%
Sth Braunstone AHO Elec	CO	87	81	107%
Tatlow Rd Comm Home Elec	SQ21	123	68	181%
The City Gallery Elec	HL1	98	70	141%
Thumby Lodge Primary Elec	SE	26	34	76%
Thurncourt EPH Elec	SQ21	103	68	151%
Town Hall Elec kWh	CO	42	111	38%
Tudor Centre Elec	CO	53	81	66%
Welford House Elec kWh	SQ10	121	33	365%
Westcotes Library Elec	HL1	31	46	67%
Whitehall Sch Main Elec	SE	34	34	101%

Table 8. Gas NPI results

Meters	Building type	Actual NPI (kWh/m2)	Typical NPI (kWh/m2)	Actual % of Typical
16 New Walk Gas	CO	75	143	53%
308 Melton Rd Gas	CO	n/a	143	n/a
31 Lower Hastings St Gas	SQ21	186	432	43%
33 Lower Hastings St Gas	SQ21	413	432	96%
38 Upper Titchbourne Gas	SQ21	169	432	39%
47 New Walk Gas	CO	125	143	87%
Abbey House EPH Gas	SQ21	413	432	96%
Arbor House EPH Gas	SQ21	329	432	76%
Ash Field School Gas	SE	268	157	171%
Attenborough House Gas	CO	n/a	143	n/a
Aylestone Les Main Gas	HL3	279	343	81%
Aylestone Library Gas	HL1	288	210	137%
Barnes Heath House Gas	SQ21	378	432	87%
Barnett Janner WAA Gas	SQ21	n/a	432	n/a
Beatty Ave B Gas	SQ21	n/a	432	n/a
Beaumanor Hostel Gas	SQ21	281	432	65%
Belgrave Library Gas	HL1	214	210	102%
Belgrave Neigh. Cent Gas	SQ10	253	187	135%
Bowder House WAA Gas	SQ21	n/a	432	n/a
Braunstone Oak NC Gas	SQ10	n/a	187	n/a
Bridges House WAA Gas	SQ21	n/a	432	n/a
Butterwick Gas	SQ21	520	432	120%
Catherine Jnr School Gas	SE	n/a	157	n/a
Central Library Gas	HL1	n/a	210	n/a
Charnwood AHO Main Gas	CO	80	143	56%
Coleman Neigh Centre Gas	SQ10	292	187	156%
Coss Fam Centre Gas	SQ10	n/a	187	n/a
Coss Pool Main Gas	HL3	856	1321	65%
Cromwell House WAA Gas	SQ21	n/a	432	n/a
Dudley House WAA Gas	SQ21	n/a	432	n/a
Elizabeth House EPH Gas	SQ21	426	432	99%
Energy Office Gas	CO	210	143	147%
Evington Library Gas	HL1	n/a	210	n/a
Fred.Thorpe WAA Gas	SQ21	n/a	432	n/a
Gumbrill House WAA Gas	SQ21	n/a	432	n/a
Heatherbrook Sch Gas	SE	166	157	106%
Helena Roberts WAA Gas	SQ21	n/a	432	n/a
Herrick Lodge EPH Gas	SQ21	n/a	432	n/a
Home Farm AHO Main Gas	CO	206	143	144%
Home Improvement Agy Gas	CO	45	143	31%
Humberstone AHO Main Gas	CO	278	143	194%
Jackson House WAA Gas	SQ21	n/a	432	n/a
Judgemeadow CC Gas	SE	104	157	66%
Lansdowne Neigh Cent Gas	SQ10	55	187	29%
Lansdowne Pre School Gas	SE	119	157	76%
Lough Rd Hostel Gas	SQ21	n/a	432	n/a
Marlborough House Gas	CO	18	160	11%
Millgate Centre Main Gas	SE	461	157	294%
Nether Hall School Gas	SE	302	157	193%
Netherhall Childrens Gas	SQ21	212	432	49%
Netherhall Neigh Cent Gas	SQ10	360	187	193%
New College Main Gas	SE	n/a	157	n/a
New Parks AHO Gas	CO	n/a	143	n/a
New Parks Les Gas	HL3	702	343	205%
New Walk B Block Gas	CO	173	160	108%
New Walk Museum Gas	HL1	168	142	118%
Norfolk House WAA Gas	SQ21	n/a	432	n/a
Nuffield House EPH Gas	SQ21	538	432	125%
Phoenix House Gas	CO	165	160	103%
Pollard House WAA Gas	SQ21	n/a	432	n/a
Preston Lodge EPH Gas	SQ21	464	432	108%
Reference Library Gas	HL1	112	210	53%
Rowsley St AHO Gas	CO	184	143	128%
Rupert Hse WAA Gas	SQ21	n/a	432	n/a
Saffron AHO Gas	CO	119	143	83%
Scraptoft Valley Prim. Gas	SE	164	157	105%
Southfields Library Gas	HL1	483	210	230%
Spence St Hall Main Gas	HL3	n/a	343	n/a
Spence St Pool Gas	HL3	689	1321	52%
St Marks AHO Main Gas	CO	n/a	143	n/a
St Saviours NC Gas	SQ10	79	187	42%
Sth Braunstone AHO Gas	CO	213	143	149%
Tatlow Rd Comm Home Gas	SQ21	314	432	73%
The City Gallery Gas	HL1	158	142	112%
Thurnby Lodge Primary Gas	SE	192	157	122%
Thurncourt EPH Gas	SQ21	372	432	86%
Town Hall Gas	CO	178	205	87%
Tudor Centre Gas	CO	68	143	48%
Welford House Gas	SQ10	93	187	50%
Westcotes Library Gas	HL1	104	210	50%
Whitehall Sch Main Gas	SE	441	157	281%

5.6. Energy data analysis in Matlab®

Matlab®, or MATrix LABoratory, is an interactive software for high performance numerical calculation, developed by Mathworks. Matlab® includes numerical analysis, matrix calculation, signal processing, and graphical data analysis. This numerical calculation software package was selected for the implementation of visual and analytical energy analysis techniques.

Other software packages could have been selected, for example Mathematica, Maple or even IDL. However, Matlab® data visualisation capabilities, the graphical user interface, and the easy integration with Microsoft® SQL Server™ 2005 database determined the selection of this software. Matlab® was extensively used in the current study, not only to conduct visual and to calculate weather and non-weather indicators, but also to clean raw data directly on the database.

The Matlab® software was running on a PC (1.6 GHz and 512 MB) with MS Windows. As described previously in this chapter, Matlab® was used to pre-process raw data in order to correct data stamps, re-sample missing data and eliminate outliers. The more complex data analysis was also conducted using Matlab®. A simple user interface was devised using Matlab® graphic interface capabilities. This interface allows manually selection of visualisation techniques and the calculation of indicators for individual meters. Figure 27 and Figure 28 presents the graphic interface for data visualisation and indicators calculation tables.

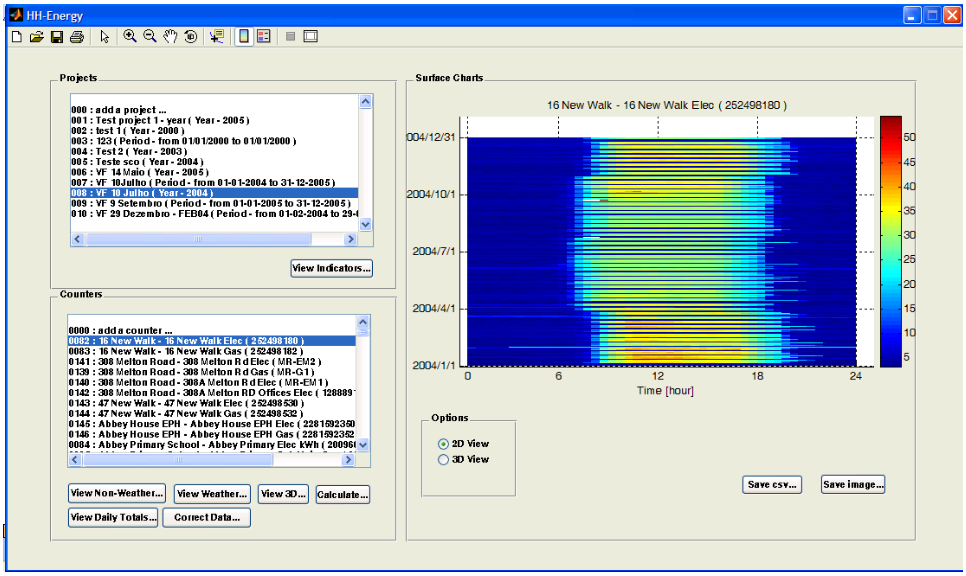


Figure 27. Energy analysis tool graphic environment – 2D data visualisation

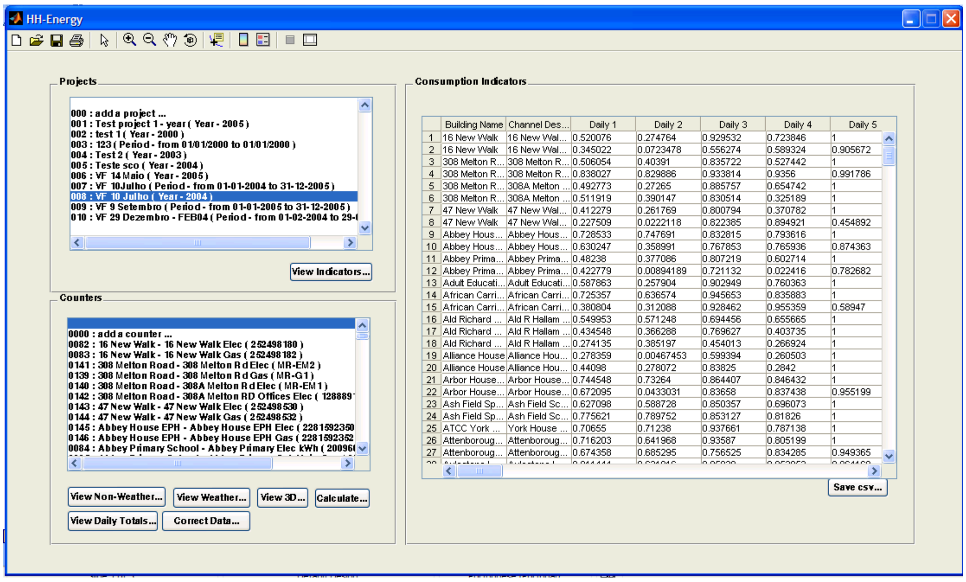


Figure 28. Energy analysis tool graphic environment – indicators calculations

The initial inputs are:

- the period of analysis (typically one year) and set to be the year 2004 in the current study,
- the buildings to analyse and individual meters channels.

The selection from individual techniques and indicator calculation is done manually by pushing buttons located in the left-hand corner. The outputs range from producing 24-hour profiles, line-plots, 2D and 3D plots, regression plots and quantitative indicators. The analysis outputs are summarised in Figure 29 diagram. For each plot type it is possible to select from different complementary options. For example, for the line plots it possible to select from daily totals, and daily mean data aggregated in monthly or weekly periods. It is also possible to include percentile analysis, and maximum and minimum values for the set periods. The preparation of 2D and 3D plots uses all the half-hourly data points for the selected period. The 24-hour profile is calculated for the mean half-hourly profile, calculated for everyday (7 days of the week), weekdays (5 working days of the week) and weekends. The 24-hour profile can be complemented by the percentile analysis, and the maximum and minimum values, similarly to what has been presented in chapter 3.

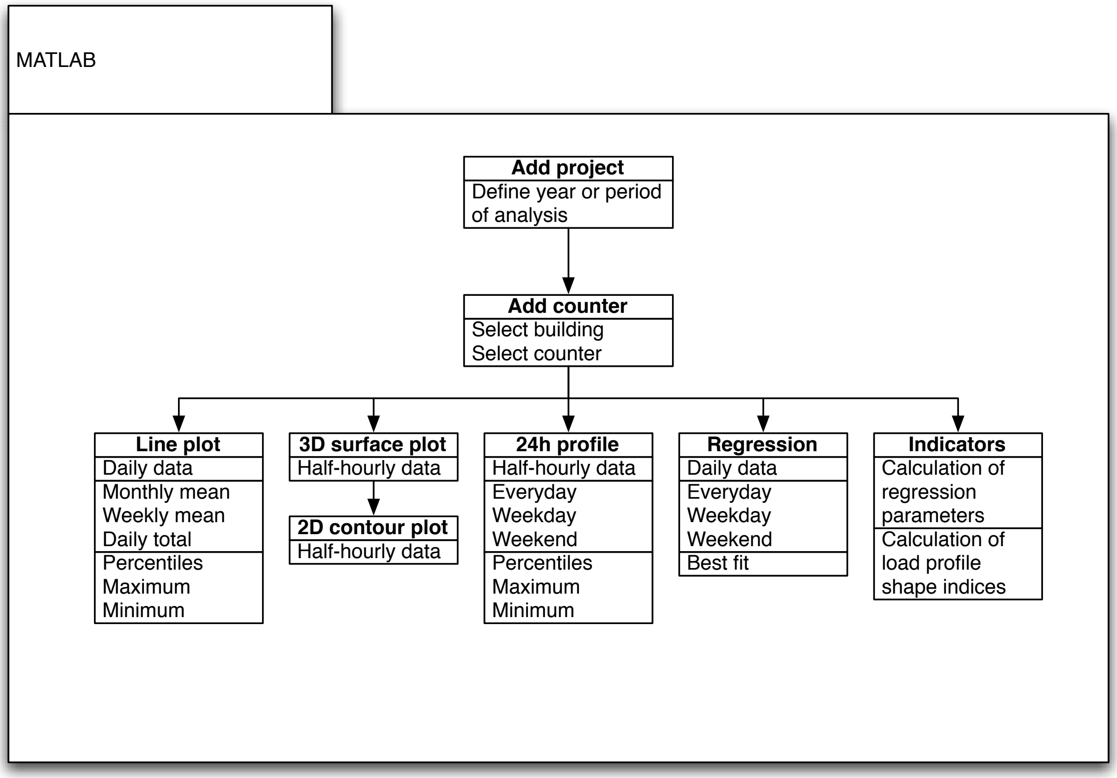


Figure 29. Matlab® functions, attributes and operations

The production of plots and indicators is a relatively time consuming process. It takes about 15 minutes to produce a complete set of plots and indicators for each meter. After completing the data cleaning process, the pre-screening of the available 404 meter-channels took about 100 hours, the time necessary to produce the required plots and indicators.

The following figure presents a diagram presenting the overview of the inputs, data analysis functions and outputs produced by the research tool developed in Matlab®. A detailed overview of the core code algorithms is offered in Appendix B.

The following chapters include a detailed presentation of the visual and analytical capabilities explored under the current work. In chapter 3 it was found that visualisation tools are used quite extensively in short time series data analysis, but offer very limited and subjective data interpretation. Therefore the focus of this research work was on the interpretation of indicators described in chapter 6 – these indicators are IMT parameters and load demand shape profile indices.

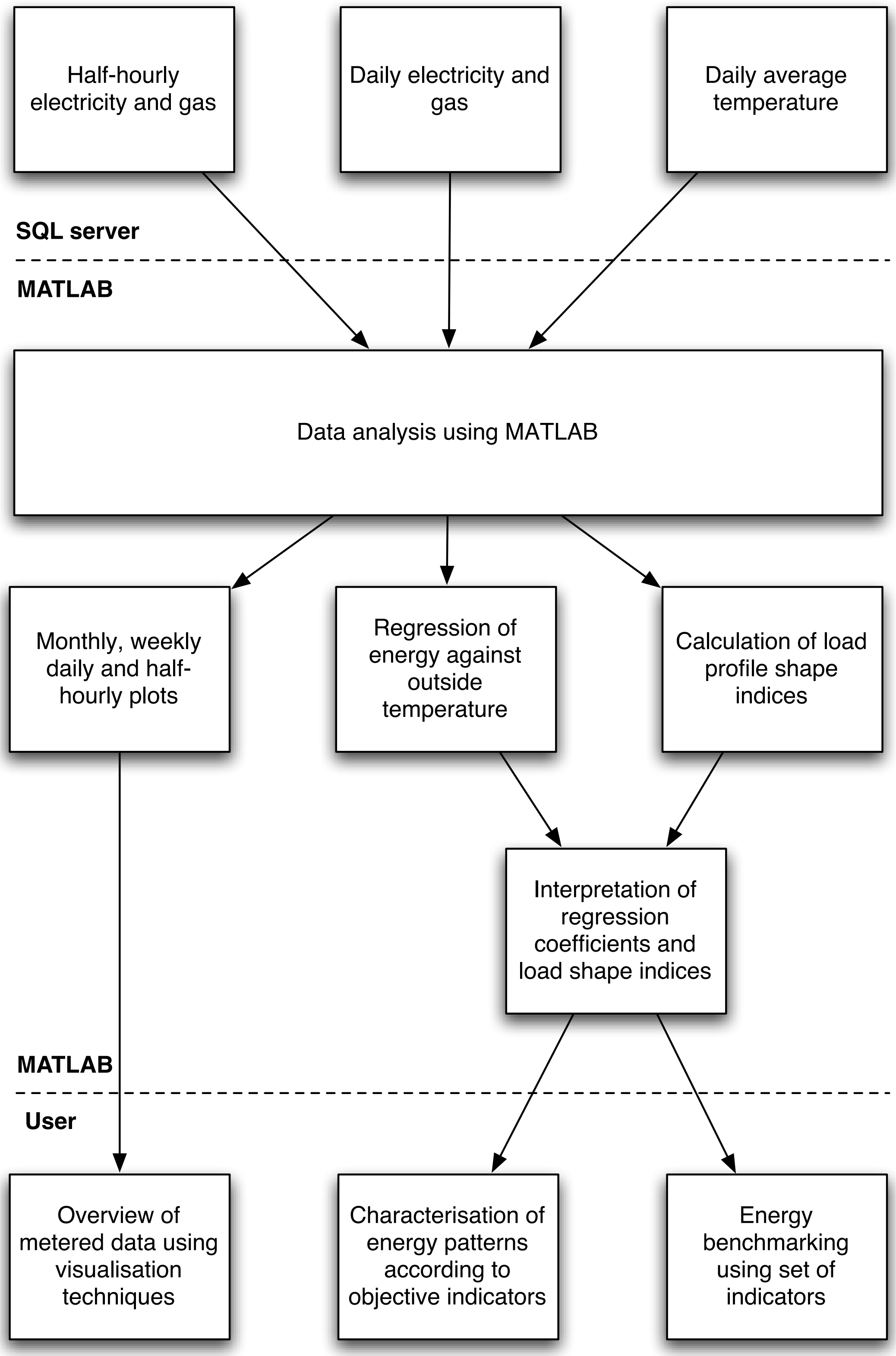


Figure 30. Schematic describing the data analysis functions

5.7. Chapter summary

Data was collected by the DATA BIRD system, a commercially available AMR system, used by local authorities and multi-site companies. Therefore, the data used in the current work is similar to data used under real conditions by practitioners in the field.

The data error correction algorithms applied by the DYNAMAT software were unknown due to commercial confidentiality issues. So, in order to avoid unspecified bias during data analysis, the option was to use the raw data directly collected from the meter by DATA BIRD. A simple algorithm was automatically applied in order to re-sample missing data and also to correct unusual 'spikes'. The procedures used were simple, and based on published Portuguese electricity sector regulator guidance (ERSE, 2003).

Outside temperature data was collected from a single weather station sensor. This data was freely available, and is the data used by Leicester to manage energy in their buildings. Furthermore, the use of only St. Peters weather station temperature sensor data was found to be suitable because all buildings under study are located near Leicester city centre. However, since this research started DMU now have a weather station. This data could be used in the future.

The 162 electricity and gas primary metering datasets (corresponding to 81 buildings) were selected from the potential 404 meter channels in the database. It was deemed necessary to apply a set of criteria to ensure that good quality data sets of primary meter electricity and gas consumption from municipal buildings were chosen.

The framework for the selection of meters and buildings was in line with the research project objectives. Conventional NPI were calculated using the available floor area. A comparative study of NPI and profile indicators is included in the discussion chapter. Note that floor area is not an input for the calculation of IMT parameters and load demand shape indicators; these indicators are independent from floor area.

The distribution of buildings through the classes, presented in Table 5 is not uniform. There are building types with a considerable number of datasets, and others with just a few. The HL3 buildings are only 5, and 10 datasets (5 for electricity and 5 for gas use). However, for other classes there are a large number of buildings. For example, CO and SQ21 buildings represent more than half of the data sets available. Statistical tests will be used to overcome limitations of available data.

The next chapter presents the theory behind the use of numerical parameters to characterise consumption profiles. These indicators will then be used to conduct benchmarking and to identify unusual energy consumption profile characteristics that can be indicative of wastage, i.e. potential energy saving opportunities.

Chapter 6. Metrics for short time-series energy data analysis

The aim of this research project was to investigate the usefulness of primary meter energy short time series data to assess performance and identify potential electricity and gas saving opportunities in buildings. Primary meter is the measurement of the total energy consumption. Short time series data corresponds to the frequency of the meter readings, and typically in the UK the meter integration period is half-hourly.

There is an increasing amount of short time series data being collected. However, energy analysis techniques currently in use, based mostly on visualisation, are not suitable to effectively analyse short time series data. It is necessary to introduce quantifiable parameters and statistics to conduct an objective measurement of energy demand profiles and consumption patterns. These parameters can contribute to deliver a systematic approach to building energy performance assessment, as much as possible, automated diagnostics in line with energy managers' needs.

This chapter presents and justifies the development of an analytical approach based on the use of numerical parameters and indicators that characterise building electricity and gas load demand profiles, and the dependency of energy use on outside temperature.

The expected outcome is a consistent, robust and comprehensive set of indicators that when applied to the analysis primary meter half-hourly electricity and gas use from municipal buildings, is able to characterise objectively and efficiently consumption profiles. These indicators were tested using empirical data from Leicester City Council buildings, presented in chapter 5. Experimental results are presented further in the text, in chapters 7, 8 and 9.

The approach suggested is composed by two groups of indicators. The first group of indicators described the buildings' daily and weekly load demand profiles, and are usually categorised as load demand shape indices. These indicators are calculated from 24-hour load demand profiles and are used to model occupancy patterns, intensity of use and baseload consumption. Following an extensive literature review, no evidence was found that load demand shape indices had been used previously in building energy management.

The second group of indicators was applied to model the relationships between energy use and outside temperature data. These indicators were derived from ASHRAE's Inverse Modelling Toolkit. IMT allowed the calculation of model parameters directly linked to building thermal behaviour. These parameters, or indicators, support the inference on weather related building energy use.

The experimental validation of these sets of quantitative indicators was an important innovation introduced in the current work. Research focused on assessing the usefulness of the application of these indicators to contribute to improve building operation and identification of potential savings. This was done through benchmarking buildings performance using available primary metered short time series electricity and gas data analysis.

All the energy indicators used in the current work are presented in detail in the following sections, the first section on daily load demand shape indices and the second section on parameters that model the relationship between energy use and outside temperature.

6.1. Half-hourly load demand profile shape indices

In the current study the characterisation of the daily mean energy (electricity and gas) demand profile was done using load curve shape indices. Daily load curve shape indices are quantitative descriptors of load demand profiles. These indices are dimensionless ratios related to the shape of the daily energy demand profile. Typically they are applied to whole-building electricity consumption profiles. Researchers and utilities have been using shape indices to classify customers, to perform electricity tariff studies and to forecast demand in power distribution networks.

According to Chicco, et al. (2001) the origin of electricity load shape indices can be found in (Ernoult & Messier, 1982). They were the first to use indices from representative daily electricity load profiles to analyse and forecast demand. Nazarko and Styczynski (1999) electricity distribution load modelling study proposes the systematisation of daily load curve shape metrics, by proposing four indices, one for each time of the day: morning, afternoon, evening and night. These indices are calculated using the 24 hour mean load demand profile calculated for weekdays only. These indices have never been applied before to gas consumption data.

The next figure presents the statistical approach suggested by Nazarko and Styczynski (1999) to model load demand profiles.

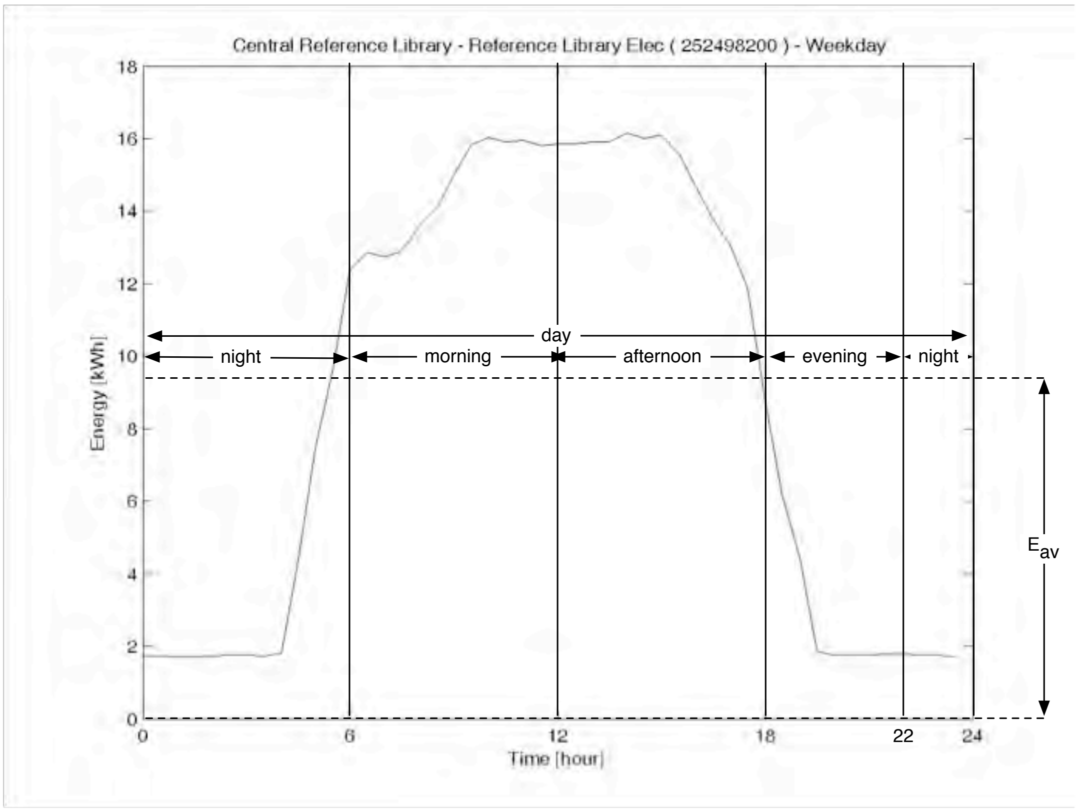


Figure 31. Electricity load demand profile model, adapted from (Nazarko & Styczynski, 1999)

The model indices can be calculated by dividing the average use in each period (night, morning, afternoon and evening) by the 24 hours daily average energy consumption or power usage. For example, the dimensionless ratio for morning hours would be defined by the following equation, where *m* is the *morning* period (6h00 to 12h00), and *d* stands for the 24 hours of the day.

$$\alpha_m = \frac{E_{m.AV}}{E_{d.AV}}$$

Equation 5. Calculation example of electricity load demand profile model indices

Nazarko and Styczynski (1999) successfully applied this model to forecast electricity demand on several domestic, commercial and industrial electricity consumers in Poland and Germany. The forecast of electricity demand is usually done for a group of consumers connected to the same medium voltage distribution network node. Load demand forecasting is an exercise based on load models and customers load demand profile characterisation that aims at providing the future demand at a given distribution network node. Based on Nazarko and Styczynski (1999) work, Chicco, et al. (2001) offers an improved set of electricity load curve shape indices for electricity load demand forecasting. This model is composed by five daily indices and three weekly indices. The daily indices characterise the baseload, peak demand, lunchtime, and night impact (on weekend and weekdays) consumption. Chicco, et al. (2002, 2003) proposed additional indicators to characterise load demand curves to classify domestic electricity customers. The main application of these indicators was to study electricity tariff offer. No evidence was found in the published literature that electricity load curve shape indicators have been used for the analysis of individual buildings performance assessment, fault detection and diagnostics, or even with short time series gas consumption data.

The final set of indicators employed in the current research work resulted from the compilation of load shape indices found in the literature, which resulted in nine daily indices and three weekly indices. These indices model the occupancy patterns of buildings, and the energy demand during expected occupied and non-occupied periods.

The calculation of load demand shape indicators included dissecting the daily demand profile in distinct periods:

- Day (*d*) the 24 hours of the day,
- Night period (*n*) period from 22h00 to 6h00,
- Office working hours (*o*) from 8h00 to 18h00,
- Lunch period (*l*) from 12h00 to 14h00.

These intervals, also presented in Figure 32 are similar to the intervals used by Chicco, et al. (2001), but slightly different to the intervals used by Nazarko and Styczynski (1999), presented in Figure 31.

The intervals used by Chicco, et al. (2001) were considered to be more appropriate to model buildings with occupied and non-occupied periods. A significant number of Leicester municipal buildings are offices and buildings open to the public (libraries, schools, community centres, etc), which have different operation schedules. However, it was decided to use a fixed occupancy period. This fixed period was defined to be from 8h00 to 18h00. The real occupancy period could be used instead, however this data was not readily available for all the buildings. So, for the sake of uniformity the office working hours period was used to compute load shape indicators for selected buildings. Similarly, the lunchtime period was set to be between 12h00 and 14h00, for the same reason. And the night period was defined to be between 22h00 and 6h00.

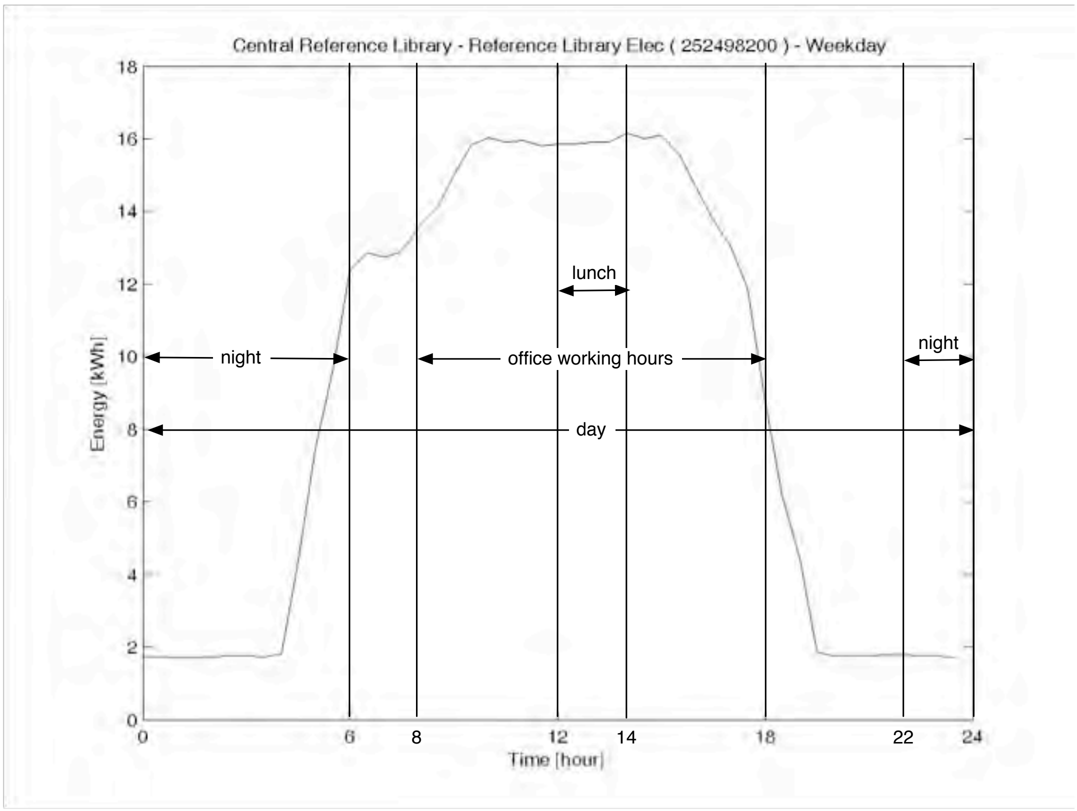


Figure 32. Electricity load demand profile model with daily periods for indicators calculation

The indicators are dimensionless ratios, computed using the average demand in daily periods defined previously, (*d, o*, *n*, *l*) presented in Figure 32 and the average (*AV*), minimum (*MIN*) and maximum (*MAX*) daily energy demand, presented in Figure 33.

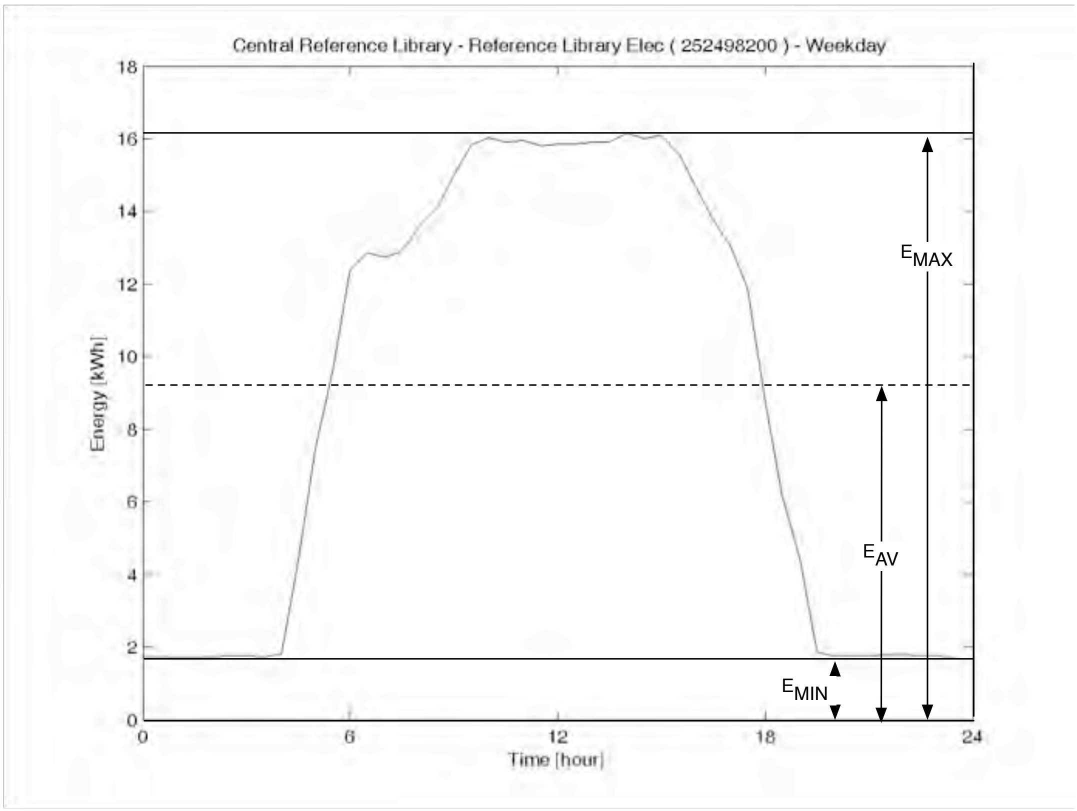


Figure 33. Electricity load profile model with energy variables for indicators calculation

The following table present the definition of the twelve load demand shape indicators included in the current work.

Table 9. List of load demand shape indices

Indicator	Short description
α_{D1}	Load factor on weekdays
α_{D2}	Modulation coefficient for baseloads calculated only for weekdays
α_{D3}	Load factor calculated for office hours (o) on weekdays only
α_{D4}	Baseload modulation coefficient for working hours on weekdays
α_{D5}	Peak demand uniformity coefficient
α_{D6}	Baseload uniformity coefficient on weekdays
α_{D7}	Night impact on weekdays
α_{D8}	Night impact on weekends
α_{D9}	Lunch impact on weekdays
α_{W1}	Weekly load factor
α_{W2}	Weekly baseload modulation coefficient
α_{W3}	Weekend impact

The following nine equations present the daily load demand shape indices. These indicators were calculated for the annual mean weekday load demand profiles, except for α_{D8} that was calculated for the mean weekend load demand profiles.

The first daily indicator, α_{D1}, in Equation 6 is the load factor for weekdays. The load factor is the ratio between the daily (*d*) average (*AV.*) energy use, and the daily maximum (*MAX.*) demand.

$$\alpha_{D1} = \frac{E_{d.AV.weekdays}}{E_{d.MAX.weekdays}}$$

Equation 6. Calculation of α_{D1} indicator – Load factor on weekdays.

Equation 7 presents indicator, α_{D2}, a modulation coefficient for baseload consumption. This indicator is the daily minimum divided by the daily average energy usage, considering the weekday load demand profile.

$$\alpha_{D2} = \frac{E_{d.MIN.weekdays}}{E_{d.AV.weekdays}}$$

Equation 7. Calculation of α_{D2} indicator – Modulation coefficient for baseloads calculated only for weekdays.

Equation 8 presents the load factor calculated for working hours only, i.e. the period from 8h00 to 18h00 .

$$\alpha_{D3} = \frac{E_{o.AV.weekdays}}{E_{o.MAX.weekdays}}$$

Equation 8. Calculation of α_{D3} indicator – Load factor calculated for office hours (o) on weekdays only.

Equation 9 presents the baseload modulation coefficient for office working hours only, i.e. the period from 8h00 to 18h00.

$$\alpha_{D4} = \frac{E_{o.MIN.weekdays}}{E_{o.AV.weekdays}}$$

Equation 9. Calculation of α_{D4} indicator – Baseload modulation coefficient for office working hours (o) on weekdays only.

Equation 10 presents the peak demand uniformity coefficient, which compares the maximum demand of the day with the maximum demand for the period between 8h00 and 18h00.

$$\alpha_{D5} = \frac{E_{o.MAX.weekdays}}{E_{d.MAX.weekdays}}$$

Equation 10. Calculation of α_{D5} indicator – Peak demand uniformity coefficient.

Equation 11 presents the baseload uniformity coefficient, which compares the minimum demand of the day with the minimum demand in the period between 8h00 and 18h00.

$$\alpha_{D6} = \frac{E_{d.MIN.weekdays}}{E_{o.MIN.weekdays}}$$

Equation 11. Calculation of α_{D6} indicator - Baseload uniformity on weekdays.

Equation 12 presents the indicator that models the overnight energy demand, in comparison with the daily average demand, considering weekdays only.

$$\alpha_{D7} = \frac{E_{n.AV.weekdays}}{E_{d.AV.weekdays}}$$

Equation 12. Calculation of α_{D7} indicator – Night impact on weekdays.

Equation 13 is a similar indicator to α_{D7}, however α_{D8} is calculated for weekends only. This indicator compares the average overnight demand with the average daily demand on the weekend load demand profile.

$$\alpha_{D8} = \frac{E_{n.AV.weekend}}{E_{d.AV.weekend}}$$

Equation 13. Calculation of α_{D8} indicator – Night impact on weekends.

Equation 14 presents the indicator that models the lunch impact on weekdays. This indicator is the ratio between the average demands for the period between 12h00 and 14h00 with the demand for the period between 8h00 and 18h00.

$$\alpha_{D9} = \frac{E_{l.AV.weekdays}}{E_{o.AV.weekdays}}$$

Equation 14. Calculation of α_{D9} indicator – Lunch impact on weekdays.

The next three equations define the weekly load demand shape indicators. The first two indicators are calculated for mean load demand profile for the 7-days of the week. Equation 15 is the load factor calculated using the maximum and average energy demand for the week. Equation 16 presents the baseload modulation also for the week. Equation 17 is the ratio between the weekend consumption and the average consumption of the 7-days of week.

$$\alpha_{W1} = \frac{E_{d.AV.week}}{E_{d.MAX.week}}$$

Equation 15. Calculation of α_{W1} indicator – Weekly load factor.

$$\alpha_{W2} = \frac{E_{d.MIN.week}}{E_{d.AV.week}}$$

Equation 16. Calculation of α_{W2} indicator – Weekly baseload modulation coefficient.

$$\alpha_{W3} = \frac{E_{d.AV.weekend}}{E_{d.AV.week}}$$

Equation 17. Calculation of α_{W3} indicator – Weekend impact.

The complete set of twelve indices offer a complete characterisation of daily and weekly demand profiles. This metric was applied for the first time to the analysis of short time series data for the purpose of assessing building energy performance. They were applied both to half-hourly electricity and half-hourly gas consumption from the selected Leicester City Council buildings. It was anticipated that the interpretation of data would benefit from the use of these indicators; mainly through the reduction of subjective judgements resulting from the visual analysis of a load energy demand line plots. It was believed that load shape indicators would allow taking forward the automation of building energy analysis, and also offer the possibility to categorise and benchmark electricity and gas profiles for UK non-domestic buildings.

No evidence was found of the application of these indices also to gas consumption data for building diagnostics. The main reason is perhaps the fact that half-hourly gas consumption data is not commonly collected by utilities. Gas consumption analysis is usually performed on a daily, weekly or even monthly basis, and is often analysed together with outside temperature data. The following section presents a set of indicators that model the relationships between buildings energy (electricity and gas) consumption and outside temperature.

6.2. Daily energy use and outside temperature data

Establishing relationship between energy use and weather conditions is an important part of the analysis of metered energy consumption data from buildings. In the current study daily total energy (electricity and gas) use was plotted against outside daily mean temperature, for a complete year of data. This is typically the period for which performance indicators are produced, mainly because it includes complete heating and non-heating seasons.

Energy against outside temperature x-y plots, are useful for visualisation of building performance in different temperature conditions. These plots can be complemented by linear regression analysis, in which coefficients are descriptors of the energy consumption dependency on ambient temperature.

The simple steady-state single-variable inverse model is the regression of total energy against average outside temperature. This model should identify the balance-point temperatures. The heating balance-point temperature is the temperature at which the building internal heat gains are similar to the building envelope heat losses. When the outside temperature is above the balance-point temperature, no space heating is required. *Mutatis mutantis* for cooling energy use.

In the simplest format, this can also be modelled by using degree-day model with a fixed base temperature, an estimated balance-point temperature, as described in chapter 2. This relation between energy and degree-days is usually labelled energy performance line (or degree-day energy signature). Not to be confused with the building energy signature, which is a plot of total daily consumption against mean outdoor temperature, which is the approach used in this thesis.

Building energy performance lines plotted with monthly energy consumption and monthly degree-days are in use for quite some time. They are documented as an energy management tool in (McVicker, 1946; Knight & Cornel, 1959; Levermore, 1995; Harris, 1989, 1992, 1999). The UK Government's energy management guidance also suggests the use of energy performance lines, and several Energy Efficiency Best Practice, Action Energy and now Carbon Trust Guides advocate the use of performance lines by energy managers in order to assess building energy performance, and to monitor and target consumption.

Harris's (1999) investigations on degree-days use in building energy management lead him to conclude on a variety of features in the energy performance lines that can be indicative of faults and energy wastage. However, the uncertainties on degree-day calculation exposed by Day (1999) lead him to propose a different method for the calculation of degree-days in CIBSE guidance on degree-days (CIBSE, 2006b). CIBSE's guide performance lines are based on Variable-Base Degree-Day (VBDD) method, presented earlier by Eto (1985) and Sonderegger, et al. (1985).

The Princeton Scorekeeping Method (PRISM) is an adaption of the VBDD method, which was firstly presented by Fels (1986), and still widely used in the US for calculation of energy savings in the residential sector. The PRISM algorithm uses the base temperature that gives the best statistical fit between energy consumption and the number of variable-base degree days in each period, usually the month. The PRISM has also been tested in non-domestic buildings, and was found to be a suitable model for monthly billing data (Eto, 1988; Haberl & Vajda, 1988; Haberl & Komor, 1990; Fels, et al., 1995; Sonderegger, 1998). However, PRISM model interpretation of the VBDD does not apply to multi-zone non-domestic air-conditioned buildings (Rabl, et al., 1992) and (Kissock, 1993).

The alternative is to use an Inverse Modelling Toolkit (IMT) with change-point models, which are able to capture the non-linear relation between heating and cooling energy use and outside temperature. The numerical algorithms of IMT are presented in detail in (Kissock, et al., 2003). IMT change-point models have been used extensively for the calculation of energy savings resulting from energy efficiency improvements in non-domestic buildings. The International Protocol Measurement and Verification of Savings (USDOE, 2002) adopted this methodology. IMT is simple to use and can be applied automatically to a large number of buildings. Additionally, IMT models have physical significance with the operation of heating and cooling equipment that is controlled by a thermostat. IMT models only require energy and temperature data inputs, and can be used with daily, weekly and monthly time scales. However, single variable steady-state models such as IMT change-point models have some disadvantages: they are not sensitive to dynamic effects of the building performance (for example, thermal mass). They are also not sensitive to variables other than outside temperature (e.g. humidity and solar radiation), (ASHRAE, 2001).

IMT models have been successfully applied to monthly energy consumption data from variety of buildings (Reddy et al., 1997), but also daily data (Haberl and Abbas, 1998b; Kissock, et al., 1998) for setting baselines and calculating energy savings from energy efficiency measures. A comprehensive presentation of IMT, including the change-point models theory can be found in (Kissock, et al., 2003), and its applications and testing in

(Haberl, et al., 2003). The Inverse Modelling Toolkit can be applied to energy use in domestic and non-domestic, and include five types of change-point models. These are presented in Figure 34 and where:

- (a) is the one-parameter model
- (b) is the two-parameter model
- (c) is the three-parameter change-point model – heating
- (d) is the three-parameter change-point model – cooling
- (e) is the four-parameter change-point model – heating
- (f) is the four-parameter change-point model – cooling
- (g) is the five-parameter change-point model

The one-parameter or constant model, can be applied when energy use is independent of outside temperature Figure 34 (a). The two-parameter change-point model, Figure 34 (b), is usually valid for buildings located in extreme weather conditions, where the heating or cooling systems operate continuously. The three-parameter change-point model in Figure 34 for both heating (c) and cooling (d) can be applied to different building types, from domestic to non-domestic, and even for gas consumption of plants supplying heat to several buildings. The four-parameter change-point model in Figure 34 (e) and (f), is usually applied to air-conditioned buildings with HVAC systems that vary their output with outside temperature (example: variable-air HVAC systems). The formulation of this model is described in Equation 18 and Equation 19. The five-parameter change-point model, in Figure 34 (g), is usually useful to model whole-building energy consumption in air-conditioned buildings that have electric heating.

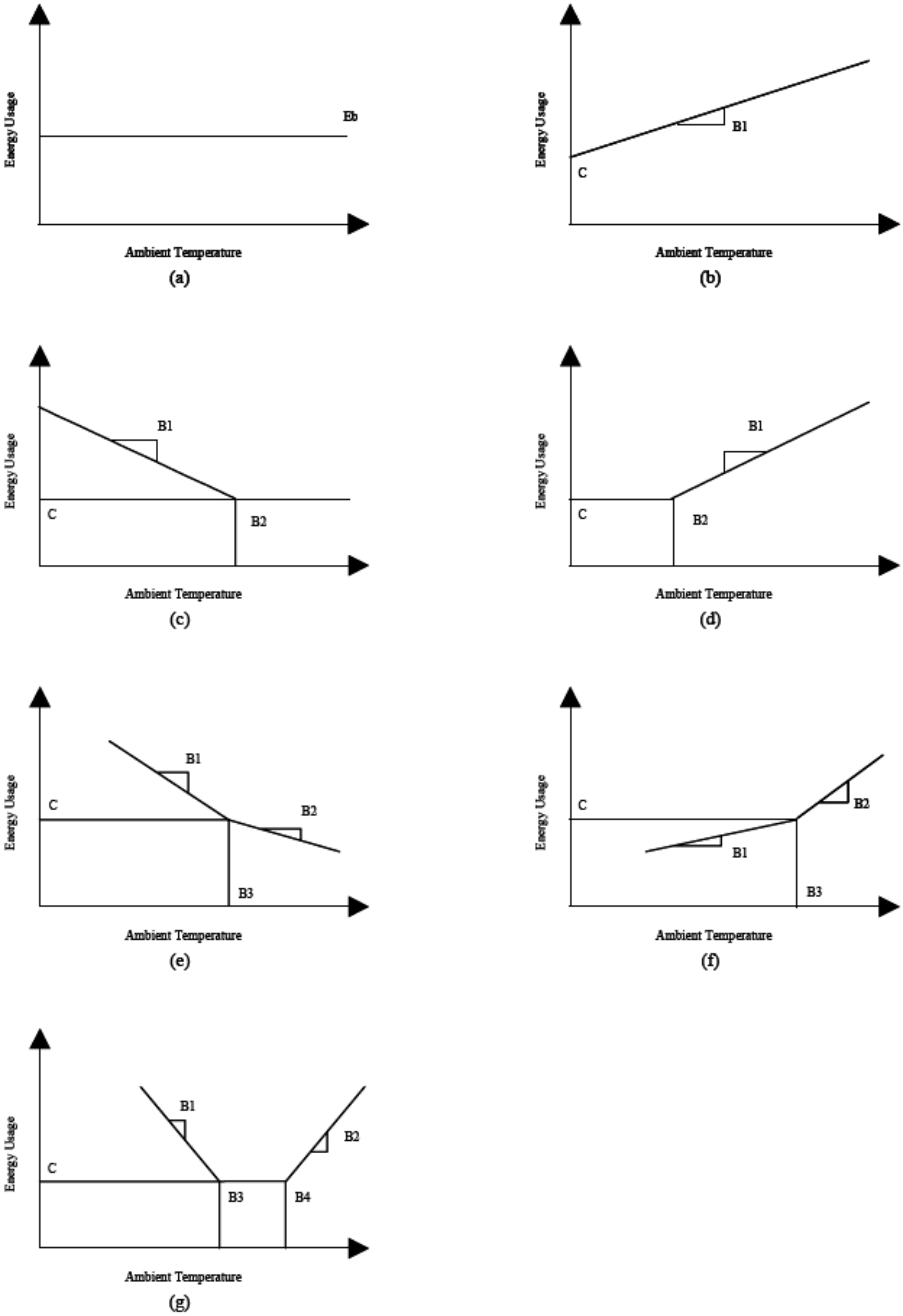


Figure 34. Energy signature change-point models, adapted from (ASHRAE, 2001)

The model type is related to the number of regression coefficients. For example the four-parameter (heating and cooling) models, includes four regression coefficients, and is described by the following equations:

$$E = c + b_1(b_3 - T)^+ - b_2(T - b_3)^+$$

where:

- c = constant energy use at the change point;
- b_1 = the coefficient that describes the linear dependency of energy with outside temperature below the change point;
- b_2 = the coefficient that describes the linear dependency of energy with outside temperature above the change point;
- b_3 = the change-point temperature;
- T = the outside temperature for the period corresponding to the energy use;
- + = only positive values inside the parentheses.

Equation 18. IMT Four-parameter heating model

$$E = c - b_1(b_3 - T)^+ + b_2(T - b_3)^+$$

where:

- c = constant energy use at the change point;
- b_1 = the coefficient that describes the linear dependency of energy with outside temperature below the change point;
- b_2 = the coefficient that describes the linear dependency of energy with outside temperature above the change point;
- b_3 = the change-point temperature;
- T = the outside temperature for the period corresponding to the energy use;
- + = only positive values inside the parentheses.

Equation 19. IMT Four-parameter cooling model

In the current study, and taking into consideration the weather conditions and the building types and HVAC systems in the UK, the three-parameter or the four-parameter change-point models for heating and cooling were probably the best suited. The three-parameter and the four-parameter models coefficients are very similar, except for the parameter b_2, which for the three-parameter is equal to zero, and is therefore excluded from the model.

However, for the four-parameter model b_2 is the slope of the curve that describes the linear dependency of energy with outside temperature above the change point. In the current study it was decided to select the four-parameter model, a more complete model that could provide insight on the building thermal behaviour above the change-point temperature.

The frequency selected for the application of the models was the day, and the period of application is 365 days, a complete year. The access to half-hourly data (electricity, gas and outside temperature) allowed the easy calculation of daily consumption and mean daily temperature. The current study was not aiming at calculating energy savings, but to assessment building performance, detecting savings and benchmarking non-domestic buildings. Therefore the parameters produced by IMT change-point models: c, b_1, b_2 and b_3 were the basis of the analysis.

Another important idea to retain is the fact that occupancy is a major factor in building energy consumption. Most of the non-domestic buildings studied are intermittently occupied. Therefore daily energy and daily mean temperature data were divided into weekdays (only Mondays to Fridays), and weekends (Saturdays and Sundays).

The four-parameter model for an example building was applied to weekdays, in Figure 35 and weekends, in Figure 36. Zero values have been removed from the plots in order to avoid bias when computing the regression parameters. From the plots it is possible to see that above a certain temperature the gas consumption is substantially reduced, and is constant (typically the non-weather related gas use is related to water heating and cooking). In the example building the model for weekdays appears to fit adequately the relationship between energy consumption and outside temperature. However, and as anticipated, the regression model does not produce the best results for weekends. This is mainly due to the fact that most of buildings under analysis operate regularly from Mondays to Fridays, and on weekends are closed or are partially occupied. It is important to note that load demand shape indicators are already modelling the energy use on weekends, and therefore consumption on Saturdays and Sundays is being considered in the analysis. Therefore IMT parameters for weekdays were found to be sufficient to model the relationship between building energy consumption and outside temperature.

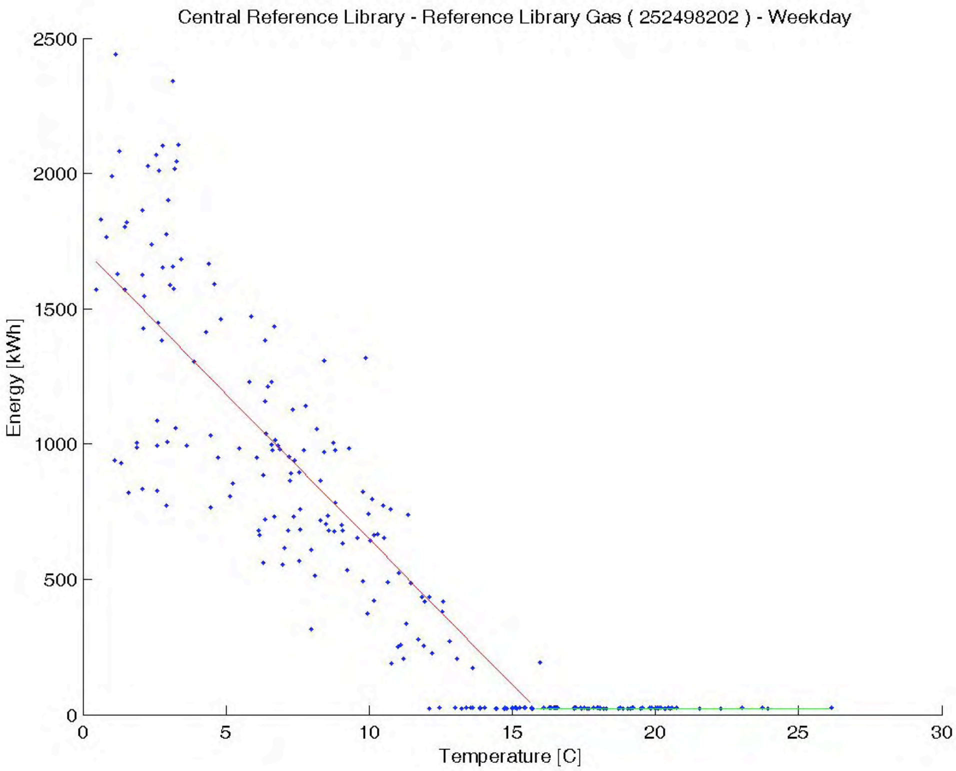


Figure 35. Example energy signature – including only weekdays

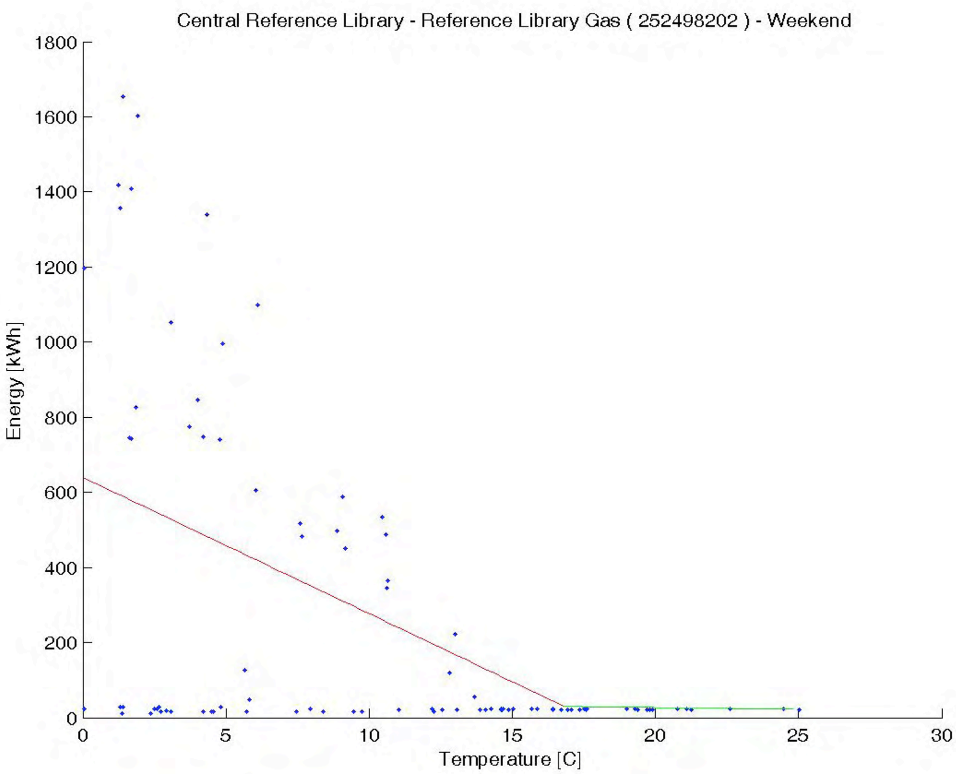


Figure 36. Example energy signature – including only weekends

6.2.1. Best fit

An important feature of the IMT change-point models is the fact that it is possible to implement an automated parameter search algorithm. This algorithm can be used to detect the best-fit lines presented in Figure 35 and Figure 36.

In statistical literature, change-point models are known as piece-wise linear regression models or spline-fits. In these models data is divided into intervals and line segments are fitted into the data in those intervals. The line segments share a common point. There are several algorithms that can be used to search for the best-fit of the line segments and common points. The change-point models of IMT use a two-stage grid search algorithm to identify the best-fit change-point developed by Kissock, et al. (1993). This algorithm has been successfully applied to three, four and five-parameter models (Kissock, 1996). Figure 37 presents the best-fit algorithm that can be applied to a four-parameter change-point models.

Using this algorithm for finding the best-fit model it was possible to automatically identify all the parameters in the models: c, b_1, b_2, b_3, and also RMSE and R^2 values for the regression lines above and below the change-point temperature, b_3.

For the example plot in Figure 35, representing the gas consumption signature of Leicester Central Reference Library for weekdays, the best-fit algorithm produced the following parameters:

- c = 22.21 kWh;
- b_1=-107.48 kWh/ºC (p-value=0.00<0.05);
- b_2=0.12 kWh/ºC (p-value=0.48>0.05);
- b_3=15.83ºC;
- $RMSE_1$= 290.58;
- $RMSE_2$=1.50;
- $R^2{}_1$=0.79;
- $R^2{}_2$=0.02.

Where $RMSE_1$ and $RMSE_2$ represent the root mean square for the regression lines before and after the change-point temperature (b_3), respectively. $R^2{}_1$ and $R^2{}_2$ are the squared correlation coefficients, before and after the change-point temperature (b_3), respectively.

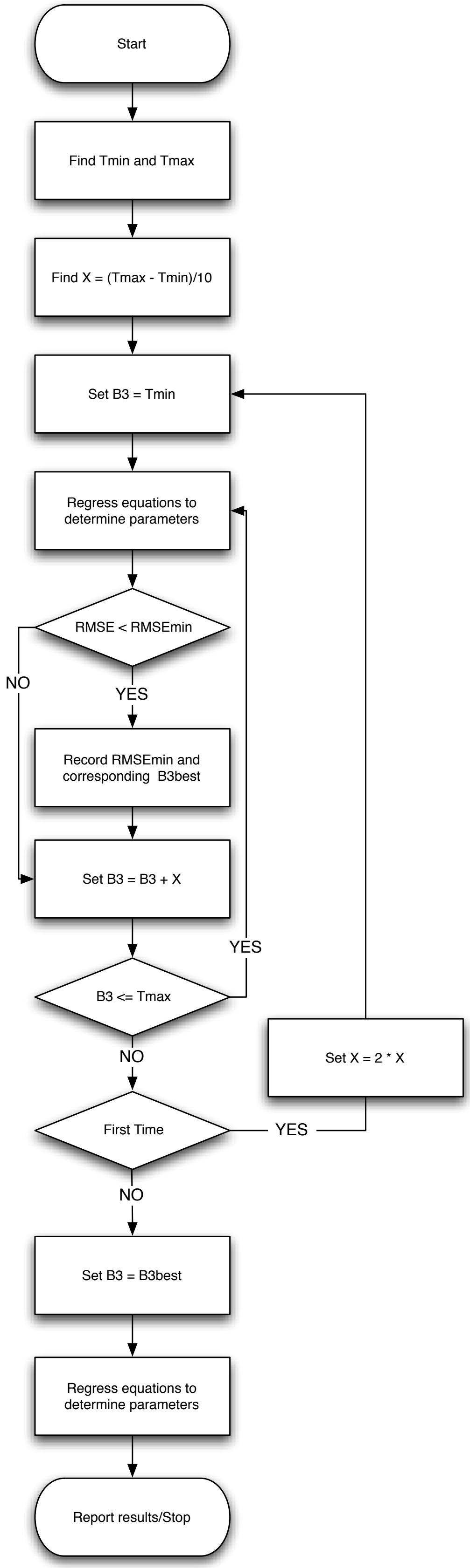


Figure 37. Four-parameter best-fit algorithm, adapted from (Kissock, et al., 2003)

6.2.2. Goodness of fit and significance of model parameters

The models in IMT use generalised least-squares regression, and coefficients are determined by minimising the sum of the squared difference between the actual (E) and predicted (Ê), determined by model regression equations. The goodness of fit of the models to the data was assessed using the root mean squared error (RMSE) and the squared correlation coefficient (R^2) for each spline (before and after the change-point). The robustness of the regression lines slopes was determined using t-tests.

RMSE is a measure of data scatter around the regression line, and can be calculated from Equation 20.

$$RMSE = \sqrt{\frac{\sum (E - \hat{E})^2}{(n - p)}}$$

Equation 20. Root mean square error

The coefficient of determination, or squared correlation coefficient, is a number between 0 and 1, and it represents the goodness of fit of the data to the regression line when compared with the mean value of the data. When R^2 is equal to 1.00 there is a perfect fit of data to the mean of the data. This coefficient can be calculated from Equation 21.

$$R^2 = 1 - \frac{\sum (E - \hat{E})^2}{\sum (E - \overline{E})^2}$$

Equation 21. Coefficient of determination

Additionally, statistical tests were performed to assess if there was a significant linear relationship between energy and outside temperature, for each regression line, before and after the change-point temperature. If this was the case then the slope was not equal zero. The hypothesis testing can be formulated for temperature values below b_3, i.e. for the first regression line as:

- H_0: $b_1 = 0$
- H_a: $b_1 \neq 0$

And, for second regression line as:

- H_0: $b_2 = 0$
- Ha: $b_2 \neq 0$

The null hypothesis considers that the slope is equal to zero, and the alternative hypothesis that the slope is not equal to zero. The t-statistic results lead to the rejection or failure to reject the null hypothesis if the p-value is below a set level of significance. The p-value measures how strong is the evidence against the null hypothesis. If the p-value is less than 0.05 (significance level) the null hypothesis is rejected. Conversely, if the p-value is more than 0.05 it is not possible to reject the null hypothesis, and it is assumed that the slope of the regression line (b_1 and/or b_2) are not significantly different from zero.

For example, for the IMT model results presented before for the Central Reference Library it is possible to conclude that slope b_1 is significantly different from zero because it is not possible to reject the null hypothesis (p-value<0.05). However the same cannot be stated for the slope b_2 for which the null hypothesis was accepted (p-value>0.05). Therefore the slope b_2 can be considered to be zero.

6.3. Chapter summary

This chapter presented the data analysis framework for the empirical research based on twelve load shape indicators and four IMT model parameters, summarised in Table 10 and Figure 38.

Table 10. List of load demand shape indices and IMT parameters

Indicator	Short description
α_{D1}	Load factor on weekdays
α_{D2}	Modulation coefficient for baseloads calculated only for weekdays
α_{D3}	Load factor calculated for office hours (o) on weekdays only
α_{D4}	Baseload modulation coefficient for working hours on weekdays
α_{D5}	Peak demand uniformity coefficient
α_{D6}	Baseload uniformity coefficient on weekdays
α_{D7}	Night impact on weekdays
α_{D8}	Night impact on weekends
α_{D9}	Lunch impact on weekdays
α_{W1}	Weekly load factor
α_{W2}	Weekly baseload modulation coefficient
α_{W3}	Weekend impact
c	Constant energy use at the change point
b_1	Dependency of energy and outside temperature below the change point
b_2	Dependency of energy and outside temperature above the change point
b_3	Change point temperature

The data analysis approach suggested by this thesis was developed based on the state-of-the-art of load demand research and building energy inverse modelling.

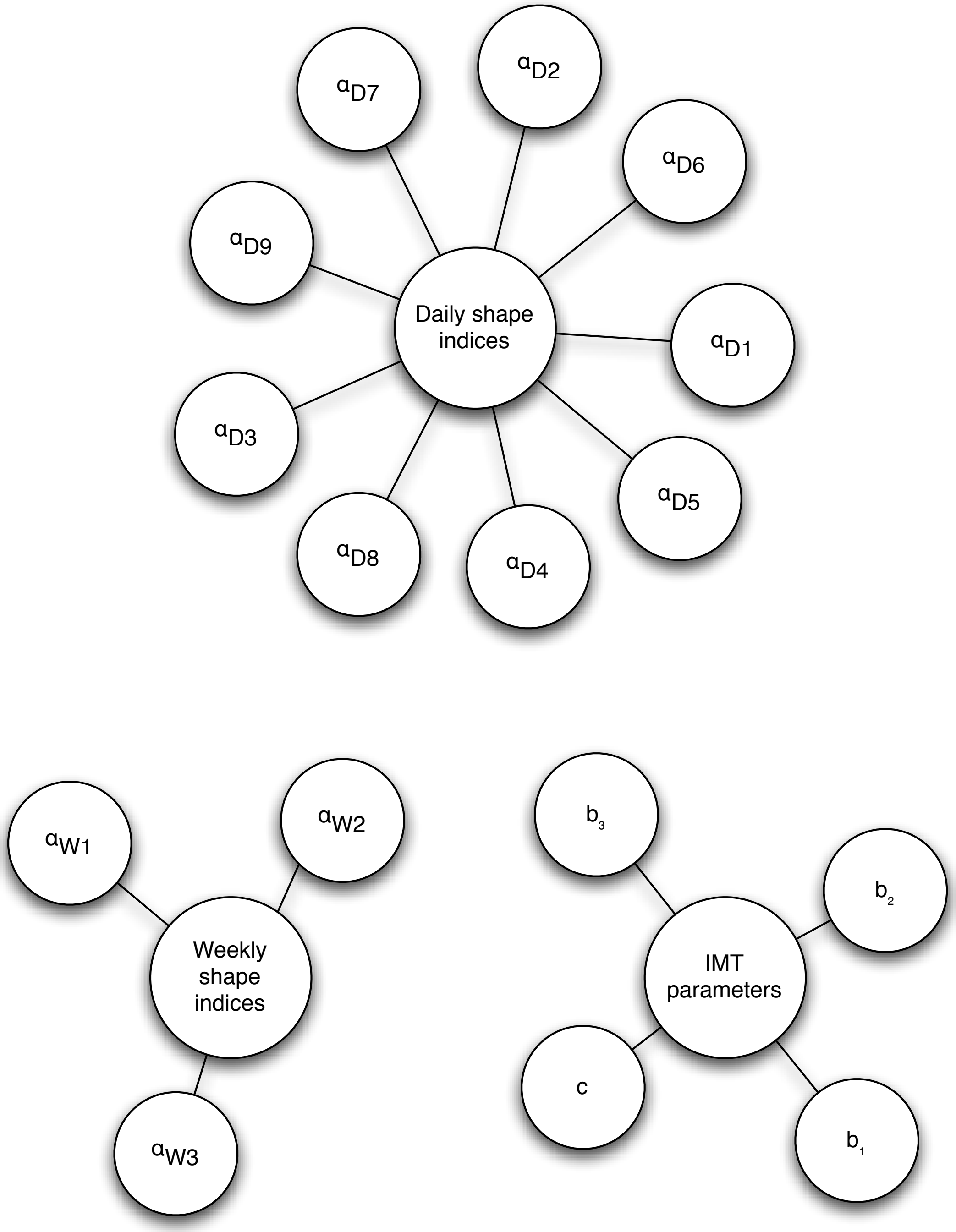


Figure 38. Load demand shape indices and IMT parameters per type

Load demand shape indicators and IMT parameters offer a quantitative characterisation of energy consumption profiles based on available short time series data. This should allow the energy practitioner to perform a rapid but comprehensive analysis of a large database of building energy consumption data, assess building energy consumption patterns, and prioritise buildings according to their typical performance. This research work is also trying to infer what type of potential energy savings can be found ‘automatically’ from the analysis of half-hourly data using the approach described in this chapter. This was investigated by exploring the benchmarking capabilities of the load demand shape indices and IMT parameters using Leicester City Council buildings half-hourly primary meter energy consumption database.

An important characteristic of the indicators under study is the fact that inputs are computed using only readily available energy and outside temperature data. Therefore this approach is independent from other data inputs required for some building energy performance methodologies, for instance floor area information, occupancy patterns, building envelope characteristics, humidity and solar radiation; data that is not always available to energy managers.

The next chapter presents the results of the application of the load demand shape indicators and IMT algorithm to the analysis of half-hourly electricity and gas data from 81 municipal buildings for the reference year.

Chapter 7. Analysis of data and interpretation of results

This chapter presents the calculation of quantitative indicators (load profile shape indices and IMT model parameters) using Leicester City Council buildings half-hourly electricity and gas data. The visualisation techniques presented earlier are used to explain the results produced by the indicators.

This chapter aims to present the results of the empirical analysis of primary energy metered short time series data in buildings. The results are presented for all the indicators and for 2004 electricity and gas data from selected buildings. It was possible to compute indicators for 81 municipal buildings, corresponding to 81 electricity meters and 81 gas meters. This analysis approach required a limited amount of data and information. Indicators were computed using one year of half-hourly energy consumption data and daily average outside temperature for the buildings location.

The first section of this chapter presents a preliminary analysis of the 12 load demand shape indicators and 4 IMT model parameters produced for each meter. In total there were 16 indicators per meter, and 32 for each building. In total 2,592 indicators values were computed to characterise the electricity and gas half-hourly primary meter consumption data of selected Leicester City Council buildings. The second section of this chapter discusses the usefulness of indicators in accomplishing the objective of the current study. A third, and final, section presents the final set of indicators, and its relation to assessing energy consumption patterns and the identification of potential opportunities to save energy.

7.1. Presentation and analysis of indicators

7.1.1. Electricity analysis

The following Table 11 contains the summary statistics of the indicators results. Table 12 presents the full results for the load demand shape indicators for electricity consumption data for all buildings.

Table 11. Summary of electricity load demand shape indices

Summary statistics	α_{D1}	α_{D2}	α_{D3}	α_{D4}	α_{D5}	α_{D6}	α_{D7}	α_{D8}	α_{D9}	α_{W1}	α_{W2}	α_{W3}
Mean	0.61	0.51	0.84	0.63	0.99	0.62	0.58	0.84	1.07	0.62	0.55	0.72
Median	0.56	0.48	0.85	0.66	1.00	0.66	0.54	0.88	1.07	0.57	0.54	0.68
Standard Deviation	0.17	0.24	0.09	0.25	0.02	0.25	0.27	0.21	0.11	0.17	0.23	0.25
Minimum	0.25	0.12	0.45	0.16	0.86	0.12	0.16	0.26	0.43	0.28	0.14	0.25
Maximum	0.95	0.98	0.98	0.99	1.00	1.00	1.03	1.19	1.28	0.96	0.98	1.02
Count	81.00	81.00	81.00	81.00	81.00	81.00	81.00	81.00	81.00	81.00	81.00	81.00

From the summary statistics table above, it is possible to observe the mean, median, standard deviation, maximum and minimum values for each load demand shape indicators. These mean values of these ratios vary from 0.51 (α_{D2}) to 1.07 (α_{D9}). Other important statistic to observe and compare to the mean values is the standard deviation. The standard deviation varies from 0.02 (α_{D5}) to 0.27 (α_{D7}), and it is usually lower than the mean.

For example α_{D1}, which represents the load factor, has low standard deviation but presents a high dispersion, the minimum value is 0.25 and the maximum value 0.95. The histogram presented in Figure 39 can help in the interpretation of this dispersion. Although α_{D1} has nearly 25 values between 0.40 and 0.50, there are few buildings for which the load factor is lower than 0.40 and a more significant number of buildings for which the load factor is above 0.50.

Conversely, indicator α_{D5} calculated for electricity demand has a very low dispersion. The histogram in Figure 40 for α_{D5} makes it clear that most results are between 0.90 and 1.00.

Table 12. Electricity load demand shape indices

Meters	α_{D1}	α_{D2}	α_{D3}	α_{D4}	α_{D5}	α_{D6}	α_{D7}	α_{D8}	α_{D9}	α_{W1}	α_{W2}	α_{W3}
308 Melton Rd Elec	0.51	0.40	0.84	0.53	1.00	0.46	0.45	0.71	1.14	0.52	0.45	0.68
16 New Walk Elec	0.52	0.27	0.93	0.72	1.00	0.21	0.29	0.98	1.06	0.54	0.34	0.35
47 New Walk Elec	0.41	0.26	0.80	0.37	1.00	0.36	0.27	1.01	1.11	0.43	0.32	0.31
Attenborough House Elec	0.72	0.64	0.94	0.81	1.00	0.61	0.69	0.86	1.06	0.76	0.68	0.86
Home Farm AHO Main Elec	0.40	0.21	0.82	0.29	1.00	0.37	0.22	0.66	1.19	0.41	0.26	0.38
Charnwood AHO Main Elec	0.38	0.33	0.71	0.22	1.00	0.77	0.34	0.92	1.06	0.40	0.40	0.42
Energy Office Elec	0.50	0.40	0.82	0.55	1.00	0.44	0.45	0.88	1.19	0.53	0.47	0.53
Home Improvement Agy Elec	0.45	0.36	0.82	0.35	1.00	0.57	0.37	1.03	1.15	0.48	0.44	0.43
Humberstone AHO Main Elec	0.46	0.30	0.87	0.34	1.00	0.46	0.32	0.78	1.13	0.46	0.36	0.50
Marlborough House Elec kWh	0.48	0.24	0.90	0.60	1.00	0.21	0.24	0.96	1.08	0.50	0.30	0.30
New Parks AHO Elec	0.52	0.45	0.87	0.32	1.00	0.86	0.49	1.00	1.15	0.55	0.52	0.56
New Walk B Block Elec kWh	0.65	0.59	0.93	0.73	1.00	0.56	0.61	0.94	1.05	0.69	0.66	0.69
Phoenix House Elec kWh	0.52	0.26	0.91	0.58	1.00	0.25	0.31	0.81	1.07	0.53	0.32	0.43
Rowsley St AHO Elec	0.46	0.46	0.79	0.43	1.00	0.61	0.46	0.98	1.08	0.50	0.54	0.54
Saffron AHO Elec	0.47	0.29	0.87	0.43	1.00	0.37	0.35	0.90	1.12	0.47	0.36	0.46
Sth Braunstone AHO Elec	0.47	0.34	0.85	0.19	1.00	0.99	0.42	1.00	1.14	0.48	0.40	0.49
St Marks AHO Main Elec	0.45	0.38	0.81	0.27	1.00	0.78	0.38	0.74	1.16	0.45	0.44	0.57
Tudor Centre Elec	0.52	0.45	0.82	0.57	1.00	0.49	0.49	1.00	1.16	0.55	0.53	0.58
Town Hall Elec kWh	0.61	0.50	0.91	0.75	1.00	0.45	0.54	0.91	1.09	0.65	0.57	0.62
New Walk Museum Elec kWh	0.57	0.58	0.86	0.56	1.00	0.68	0.59	0.72	1.14	0.56	0.61	0.86
The City Gallery Elec	0.40	0.16	0.82	0.28	1.00	0.28	0.17	0.29	1.21	0.40	0.18	0.66
Aylestone Library Elec	0.25	0.24	0.45	0.16	1.00	0.87	0.25	0.27	0.43	0.28	0.25	0.95
Belgrave Library Elec	0.48	0.14	0.90	0.42	1.00	0.17	0.20	0.37	1.07	0.46	0.16	0.57
Central Library Elec kWh	0.55	0.17	0.96	0.82	1.00	0.12	0.26	0.42	1.04	0.54	0.20	0.57
Reference Library Elec	0.55	0.19	0.94	0.78	1.00	0.14	0.31	0.51	1.05	0.55	0.22	0.58
Evington Library Elec	0.44	0.14	0.84	0.42	1.00	0.17	0.16	0.26	0.96	0.45	0.16	0.66
Southfields Library Elec	0.47	0.24	0.82	0.62	1.00	0.22	0.25	0.59	1.19	0.46	0.28	0.48
Westcotes Library Elec	0.48	0.15	0.91	0.40	1.00	0.20	0.17	0.41	1.09	0.46	0.19	0.50
Aylestone Les Main Elec kWh	0.81	0.62	0.96	0.95	0.96	0.57	0.74	0.76	1.01	0.84	0.63	0.98
New Parks Les Main Elec kWh	0.78	0.66	0.90	0.93	0.96	0.64	0.73	0.76	1.01	0.81	0.68	0.95
Spence St Hall Main Elec	0.55	0.12	0.89	0.34	0.94	0.24	0.18	0.28	1.10	0.52	0.14	0.67
Coss Pool Elec kWh	0.84	0.66	0.98	0.95	0.98	0.60	0.75	0.81	1.01	0.83	0.68	0.93
Spence St Pool Elec kWh	0.83	0.58	0.98	0.99	1.00	0.50	0.66	0.72	1.01	0.81	0.60	0.93
Lansdowne Pre School Elec	0.42	0.31	0.78	0.22	1.00	0.76	0.32	0.98	1.25	0.45	0.39	0.38
Catherine Jnr School Elec	0.43	0.45	0.73	0.34	1.00	0.80	0.46	1.02	1.24	0.47	0.54	0.54
Heatherbrook Sch Elec	0.41	0.34	0.71	0.43	1.00	0.45	0.41	1.11	1.10	0.44	0.42	0.47
Scraptoft Valley Prim. Elec	0.43	0.32	0.70	0.28	1.00	0.71	0.49	1.13	1.13	0.45	0.39	0.43
Thurnby Lodge Primary Elec	0.38	0.27	0.71	0.22	1.00	0.67	0.33	1.07	1.28	0.40	0.34	0.33
Whitehall Sch Main Elec	0.42	0.33	0.76	0.37	1.00	0.50	0.35	1.07	1.15	0.45	0.40	0.35
Judgemeadow CC Elec kWh	0.47	0.28	0.78	0.54	1.00	0.31	0.33	0.91	1.21	0.49	0.34	0.38
New College Main Elec kWh	0.50	0.45	0.81	0.48	1.00	0.58	0.48	0.94	1.15	0.53	0.53	0.56
Ash Field School Elec	0.63	0.59	0.85	0.70	1.00	0.62	0.72	1.14	1.09	0.67	0.67	0.49
Millgate Centre Elec kWh	0.57	0.53	0.85	0.66	1.00	0.53	0.54	0.97	1.13	0.60	0.59	0.58
Nether Hall School Elec	0.49	0.48	0.74	0.35	1.00	0.89	0.55	0.96	1.09	0.53	0.55	0.65
Coss Fam Centre Elec	0.40	0.18	0.79	0.27	1.00	0.34	0.23	0.98	1.23	0.41	0.24	0.25
Belgrave Neigh. Cent Elec	0.58	0.33	0.81	0.68	1.00	0.36	0.50	0.60	1.18	0.61	0.36	0.81
Braunstone Oak NC Elec	0.56	0.36	0.88	0.54	1.00	0.42	0.36	0.86	1.09	0.56	0.43	0.49
Coleman Neigh Cent Elec	0.56	0.41	0.85	0.65	1.00	0.41	0.43	0.73	1.07	0.57	0.46	0.64
Lansdowne Neigh Cent Elec	0.42	0.34	0.68	0.22	1.00	0.99	0.37	0.56	1.22	0.43	0.38	0.64
Netherhall Neigh Cent Elec	0.49	0.56	0.67	0.48	1.00	0.86	0.63	0.83	1.09	0.48	0.60	0.81
St Saviours NC Elec	0.53	0.18	0.69	0.33	1.00	0.43	0.94	1.19	1.21	0.50	0.22	0.85
Welford House Elec kWh	0.55	0.35	0.92	0.66	1.00	0.32	0.40	0.83	1.05	0.57	0.41	0.50
Abbey House EPH Elec	0.73	0.75	0.83	0.79	1.00	0.82	0.85	0.87	1.03	0.73	0.75	0.97
Arbor House EPH Elec	0.74	0.73	0.86	0.85	1.00	0.75	0.82	0.84	1.05	0.76	0.73	0.98
Barnes Heath House Elec	0.87	0.81	0.88	0.88	1.00	0.91	1.03	1.03	1.06	0.87	0.83	1.01
Barnett Janner WAA Elec	0.79	0.85	0.89	0.93	1.00	0.81	0.86	0.87	0.97	0.80	0.85	1.00
Beatty Ave B Elec	0.95	0.98	0.96	0.97	1.00	0.99	0.99	1.00	1.03	0.96	0.98	0.99
Beaumanor Hostel Elec	0.64	0.48	0.80	0.82	0.90	0.51	0.62	0.64	0.98	0.69	0.48	0.97
Bowder House WAA Elec	0.76	0.91	0.80	0.88	1.00	0.98	0.94	0.97	0.92	0.80	0.92	0.97
Bridges House WAA Elec	0.72	0.69	0.86	0.86	1.00	0.67	0.79	0.78	1.01	0.73	0.69	1.00
Butterwick Elec	0.88	0.84	0.86	0.87	0.99	1.00	1.03	1.03	1.02	0.89	0.84	1.00
Cromwell House WAA Elec	0.94	0.96	0.95	0.95	1.00	1.00	0.98	0.99	0.99	0.95	0.97	1.02
Dudley House WAA Elec	0.79	0.75	0.90	0.94	1.00	0.70	0.82	0.83	0.99	0.78	0.76	0.99
Elizabeth House EPH Elec	0.75	0.80	0.84	0.84	1.00	0.86	0.87	0.88	1.03	0.76	0.81	0.99
Fred.Thorpe WAA Elec	0.83	0.72	0.94	0.90	1.00	0.71	0.88	0.88	0.98	0.84	0.73	0.99
Gumbrill House WAA Elec	0.93	0.93	0.96	0.97	1.00	0.93	0.96	0.96	0.99	0.95	0.94	0.99
Helena Roberts WAA Elec	0.61	0.80	0.72	0.79	1.00	0.87	0.82	0.89	0.87	0.65	0.83	0.94
Herrick Lodge EPH Elec	0.72	0.71	0.89	0.87	1.00	0.66	0.76	0.82	1.03	0.74	0.73	0.94
Jackson House WAA Elec	0.82	0.79	0.93	0.94	0.99	0.75	0.83	0.84	0.96	0.82	0.79	0.99
Lough Rd Hostel Elec	0.80	0.76	0.95	0.92	0.86	0.81	0.94	0.96	1.00	0.81	0.76	0.97
31 Lower Hastings St Elec	0.79	0.59	0.88	0.81	0.97	0.67	0.83	0.82	1.03	0.78	0.59	1.01
33 Lower Hastings St Elec	0.76	0.71	0.82	0.87	1.00	0.75	0.85	0.87	0.94	0.79	0.72	0.98
Netherhall Childrens Elec	0.61	0.69	0.65	0.79	1.00	0.81	0.83	0.85	0.87	0.65	0.70	0.99
Norfolk House WAA Elec	0.85	0.94	0.88	0.91	1.00	0.99	0.97	0.97	0.97	0.88	0.95	1.00
Nuffield House EPH Elec	0.68	0.62	0.80	0.79	1.00	0.67	0.77	0.80	0.95	0.70	0.62	0.97
Pollard House WAA Elec	0.75	0.74	0.90	0.92	1.00	0.66	0.76	0.77	0.99	0.76	0.75	0.99
Preston Lodge EPH Elec	0.69	0.64	0.84	0.77	1.00	0.68	0.80	0.85	1.10	0.70	0.66	0.98
Rupert Hse WAA Elec	0.87	0.93	0.90	0.91	1.00	1.00	0.98	1.01	0.98	0.90	0.94	0.97
Tatlow Rd Comm Home Elec	0.80	0.88	0.86	0.84	1.00	0.98	0.96	1.02	1.12	0.85	0.90	0.94
Thurncourt EPH Elec	0.66	0.74	0.75	0.65	1.00	1.00	0.93	1.00	1.24	0.69	0.75	0.96
38 Upper Titchbourne Elec	0.80	0.75	0.85	0.88	1.00	0.81	0.92	0.93	1.04	0.84	0.76	0.99

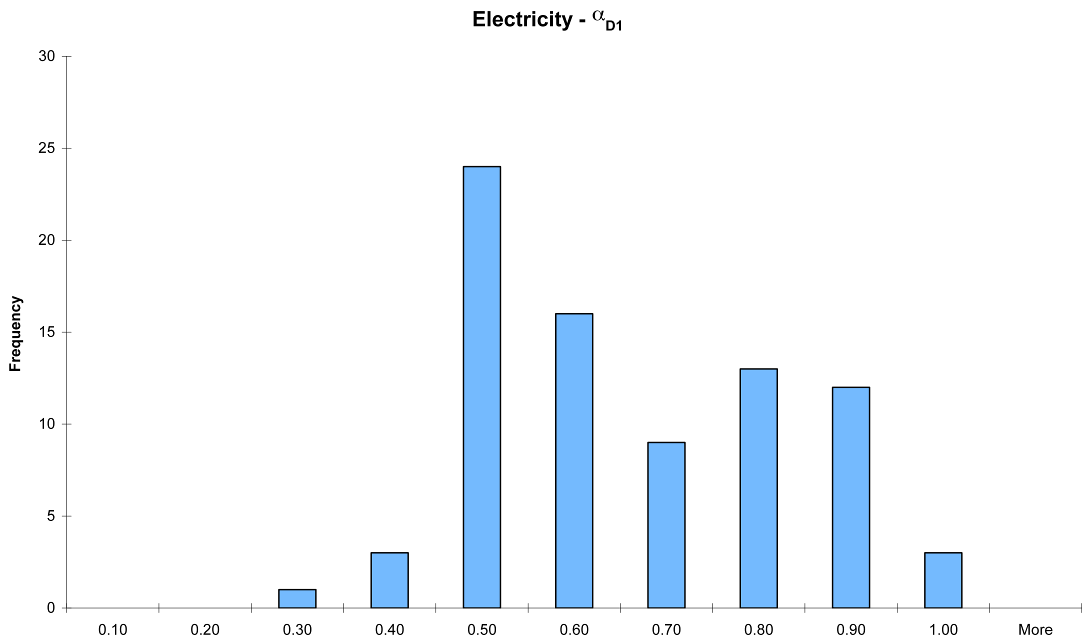


Figure 39. Histogram of electricity α_{D1} load shape indicator

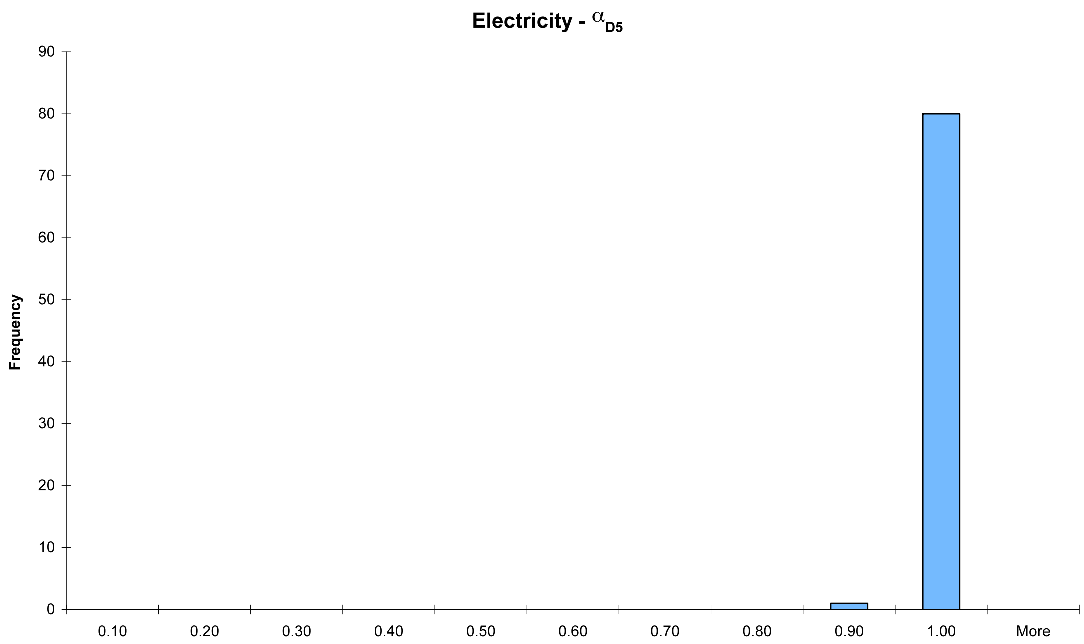


Figure 40. Histogram of electricity α_{D5} load shape indicator

Table 13 contains summary statistics of indicators results presented in Table 14 that presents the full results for the IMT model parameters applied to electricity consumption data of the selected buildings.

Table 13. Summary of electricity IMT model parameters

Summary statistics	c	b_1	b_2	b_3	$RMSE_1$	$RMSE_2$	R_1^2	R_2^2
Mean	7986.96	-36.57	187.59	20.96	2476.12	1035.56	0.18	0.20
Median	147.24	-1.18	1.58	21.56	28.53	10.84	0.13	0.11
Standard Deviation	68557.60	288.64	1627.55	7.37	21650.73	8992.83	0.17	0.22
Minimum	10.45	-2600.71	-42.60	0.46	4.79	0.55	0.00	0.00
Maximum	617356.00	12.90	14652.20	55.40	194925.00	80969.50	0.65	0.89
Count	81.00	81.00	81.00	81.00	81.00	81.00	81.00	81.00

The correlation coefficients statistics demonstrate very low mean values for both R_1^2 and R_2^2. The histogram presented in Figure 41 makes clear that daily electricity consumption is not very well correlated to mean daily outside temperature for most of the buildings, considering that R_1^2 represents the strength of the linear relation between these two variables. R_1^2 is above 0.70 for only 2 in a total of 81 datasets.

From Table 14 is also possible to see that p-values for the slope of the two regression lines, b_1 and b_2 are above the level of significance for 20 and 73 datasets, respectively. IMT parameters that were found to be above this level (p-values above 0.05) are not statistical significant, and can not be used to model the relationship between electricity consumption and outside temperature.

Table 14. Electricity IMT model parameters

Meters	c	b_1	b_2	b_3	$RMSE_1$	$RMSE_2$	R_1^2	R_2^2	p-value(b_1)	p-value(b_2)
308 Melton Rd Elec	249.97	-3.09	1.70	17.63	46.34	27.01	0.13	0.01	0.00	0.86
16 New Walk Elec	749.27	-5.69	0.62	17.94	124.18	13.83	0.06	0.00	0.00	0.90
47 New Walk Elec	617356.00	-2600.71	14652.20	10.77	194925.00	80969.50	0.00	0.02	0.89	0.71
Attenborough House Elec	1965.16	-16.96	-42.60	23.76	155.40	83.04	0.28	0.36	0.00	0.21
Home Farm AHO Main Elec	75.03	-0.48	1.39	18.83	16.25	10.25	0.03	0.04	0.01	0.71
Charnwood AHO Main Elec	49.12	0.22	4.98	19.77	12.98	8.74	0.01	0.49	0.20	0.00
Energy Office Elec	82.54	-0.14	2.20	22.94	12.74	3.35	0.00	0.48	0.33	0.13
Home Improvement Agy Elec	28.28	-0.14	-0.58	22.77	5.26	2.65	0.02	0.09	0.02	0.56
Humberstone AHO Main Elec	62.49	-0.15	2.44	16.78	11.23	10.13	0.00	0.21	0.44	0.00
Marlborough House Elec kWh	541.73	-3.78	18.69	21.55	106.93	9.37	0.04	0.89	0.00	0.00
New Parks AHO Elec	147.24	0.05	10.19	19.94	22.33	15.49	0.00	0.48	0.84	0.13
New Walk B Block Elec kWh	5315.39	11.44	246.28	19.43	566.20	367.52	0.01	0.49	0.07	0.12
Phoenix House Elec kWh	463.83	4.31	5.17	0.46	88.11	48.32	0.07	0.02	0.00	0.77
Rowsley St AHO Elec	23.58	0.37	-0.49	3.92	4.79	5.21	0.00	0.20	0.74	0.00
Saffron AHO Elec	90.27	-1.71	-2.37	55.40	31.14	7.82	0.09	0.16	0.00	0.43
Sth Braunstone AHO Elec	61.68	-0.67	1.66	22.02	11.23	3.87	0.10	0.28	0.00	0.28
St Marks AHO Main Elec	77.58	-0.43	7.05	22.45	14.19	6.87	0.03	0.69	0.01	0.04
Tudor Centre Elec	134.51	-1.18	1.84	21.61	35.59	16.08	0.03	0.03	0.00	0.76
Town Hall Elec kWh	671.24	-18.07	-0.39	18.94	159.72	25.38	0.29	0.00	0.00	0.97
New Walk Museum Elec kWh	921.41	-11.66	21.76	12.62	171.42	124.47	0.08	0.12	0.00	0.01
The City Gallery Elec	156.50	0.32	9.97	21.98	35.02	31.36	0.00	0.18	0.41	0.41
Aylestone Library Elec	10.45	-0.17	-0.31	21.23	6.95	3.81	0.02	0.01	0.03	0.82
Belgrave Library Elec	98.54	-0.56	-1.87	32.86	60.68	40.38	0.00	0.01	0.48	0.68
Central Library Elec kWh	512.59	-0.75	2.69	15.50	81.33	17.83	0.00	0.05	0.40	0.68
Reference Library Elec	396.98	-2.57	10.18	21.43	72.29	25.73	0.04	0.25	0.00	0.31
Evington Library Elec	63.56	-2.99	-0.54	15.41	15.51	4.92	0.55	0.02	0.00	0.77
Southfields Library Elec	90.93	-5.34	-2.07	22.38	53.72	15.33	0.24	0.04	0.00	0.71
Westcotes Library Elec	101.56	-0.20	0.31	31.08	19.88	5.31	0.00	0.01	0.37	0.87
Aylestone Les Main Elec kWh	2643.17	12.90	-20.29	23.50	214.87	82.41	0.10	0.11	0.00	0.51
New Parks Les Main Elec kWh	1068.75	8.36	-12.02	24.07	91.74	63.81	0.21	0.07	0.00	0.61
Spence St Hall Main Elec	95.04	-0.48	0.24	27.80	28.75	12.67	0.01	0.00	0.13	0.96
Coss Pool Elec kWh	1105.60	-1.11	-10.99	21.92	72.80	43.32	0.01	0.12	0.17	0.50
Spence St Pool Elec kWh	1003.58	6.50	-8.46	22.46	107.75	30.86	0.11	0.14	0.00	0.47
Lansdowne Pre School Elec	61.67	-1.41	-1.06	4.71	15.33	4.89	0.22	0.09	0.00	0.56
Catherine Jnr School Elec	125.86	-17.24	18.14	21.56	123.87	94.91	0.39	0.07	0.00	0.61
Heatherbrook Sch Elec	116.04	-13.64	6.90	20.18	102.81	65.40	0.31	0.03	0.00	0.36
Scraptoft Valley Prim. Elec	129.61	-27.78	5.36	19.09	137.49	65.73	0.51	0.02	0.00	0.47
Thurnby Lodge Primary Elec	174.97	-15.14	17.16	22.65	152.56	98.13	0.24	0.06	0.00	0.64
Whitehall Sch Main Elec	171.22	-13.14	11.46	22.58	136.64	90.39	0.23	0.03	0.00	0.73
Judgemeadow CC Elec kWh	663.47	-54.90	79.74	22.31	530.86	382.71	0.26	0.08	0.00	0.58
New College Main Elec kWh	709.13	-34.89	32.82	22.20	338.50	265.76	0.21	0.04	0.00	0.28
Ash Field School Elec	252.26	-20.77	19.34	22.27	142.13	128.07	0.41	0.05	0.00	0.68
Millgate Centre Elec kWh	384.42	-26.24	26.55	21.12	176.95	128.60	0.42	0.08	0.00	0.58
Nether Hall School Elec	73.32	-27.99	15.35	20.50	117.69	60.04	0.65	0.12	0.00	0.50
Coss Fam Centre Elec	51.98	-1.18	-0.61	7.75	15.68	1.73	0.11	0.31	0.00	0.63
Belgrave Neigh. Cent Elec	449.85	-8.66	-3.92	12.54	66.25	19.44	0.36	0.08	0.00	0.59
Braunstone Oak NC Elec	103.11	-0.60	12.23	23.09	36.49	21.88	0.01	0.40	0.14	0.18
Coleman Neigh Cent Elec	87.86	-0.77	-0.49	0.46	20.71	12.12	0.04	0.00	0.00	0.91
Lansdowne Neigh Cent Elec	20.34	-3.64	4.24	20.80	25.52	8.22	0.40	0.36	0.00	0.21
Netherhall Neigh Cent Elec	49.45	-0.70	-0.02	21.36	13.87	6.53	0.08	0.00	0.00	0.99
St Saviours NC Elec	48.38	-15.07	6.82	20.02	68.14	21.30	0.61	0.18	0.00	0.40
Welford House Elec kWh	1359.65	1.30	34.43	20.15	163.21	56.14	0.00	0.44	0.47	0.15
Abbey House EPH Elec	310.99	-2.93	-3.56	22.27	20.38	13.29	0.40	0.13	0.00	0.48
Arbor House EPH Elec	468.00	-3.00	3.39	24.26	28.53	16.73	0.26	0.08	0.00	0.59
Barnes Heath House Elec	259.76	-0.12	2.45	27.75	16.28	10.24	0.00	0.11	0.49	0.52
Barnett Janner WAA Elec	115.51	-1.18	1.98	21.69	8.13	3.31	0.41	0.43	0.00	0.16
Beatty Ave B Elec	60.66	-0.70	0.11	22.31	4.96	0.55	0.39	0.07	0.00	0.60
Beaumanor Hostel Elec	105.45	-2.10	5.51	21.53	13.41	8.69	0.44	0.46	0.00	0.14
Bowder House WAA Elec	122.86	-0.28	-0.01	35.85	16.18	3.36	0.01	0.00	0.12	0.99
Bridges House WAA Elec	102.70	-0.30	-2.96	22.18	17.05	12.01	0.01	0.11	0.12	0.51
Butterwick Elec	117.97	-9.33	-3.45	14.38	87.18	7.34	0.27	0.32	0.00	0.24
Cromwell House WAA Elec	147.46	-1.73	0.50	27.58	203.95	0.89	0.00	0.40	0.44	0.18
Dudley House WAA Elec	163.87	1.15	0.38	8.24	15.60	4.89	0.15	0.01	0.00	0.83
Elizabeth House EPH Elec	372.07	-0.80	2.55	17.82	22.80	10.25	0.04	0.12	0.00	0.51
Fred.Thorpe WAA Elec	157.61	-0.78	1.35	24.11	6.32	1.58	0.33	0.61	0.00	0.07
Gumbrill House WAA Elec	190.23	-0.79	1.62	23.60	8.12	1.80	0.24	0.63	0.00	0.06
Helena Roberts WAA Elec	84.44	-1.07	1.58	21.33	6.50	2.97	0.47	0.38	0.00	0.20
Herrick Lodge EPH Elec	334.90	-1.93	-3.01	30.49	21.80	7.51	0.20	0.25	0.00	0.31
Jackson House WAA Elec	237.88	4.58	0.52	19.00	49.84	7.30	0.22	0.01	0.00	0.85
Lough Rd Hostel Elec	109.24	-1.70	-3.69	31.35	12.43	7.70	0.38	0.33	0.00	0.23
31 Lower Hastings St Elec	41.07	-0.68	0.03	19.85	8.18	3.43	0.18	0.00	0.00	0.98
33 Lower Hastings St Elec	146.59	-1.93	4.96	20.46	16.06	9.78	0.32	0.35	0.00	0.21
Netherhall Childrens Elec	90.86	-1.44	16.00	22.89	30.97	19.25	0.07	0.60	0.00	0.07
Norfolk House WAA Elec	173.83	-0.51	0.91	24.64	7.05	5.69	0.15	0.05	0.00	0.66
Nuffield House EPH Elec	269.54	-5.10	4.09	21.95	25.59	10.84	0.56	0.23	0.00	0.33
Pollard House WAA Elec	195.89	-0.70	-3.98	23.23	6.95	4.13	0.25	0.66	0.00	0.05
Preston Lodge EPH Elec	396.83	-7.48	-14.53	28.47	88.24	9.44	0.19	0.83	0.00	0.01
Rupert Hse WAA Elec	163.73	-1.35	-2.49	21.18	15.82	7.27	0.19	0.20	0.00	0.37
Tatlow Rd Comm Home Elec	108.53	-0.56	0.28	17.26	8.88	3.69	0.12	0.01	0.00	0.83
Thurncourt EPH Elec	380.74	-2.47	1.96	25.11	21.06	13.35	0.31	0.04	0.00	0.69
38 Upper Titchbourne Elec	68.05	-0.21	-1.12	20.83	10.16	4.22	0.01	0.13	0.06	0.48

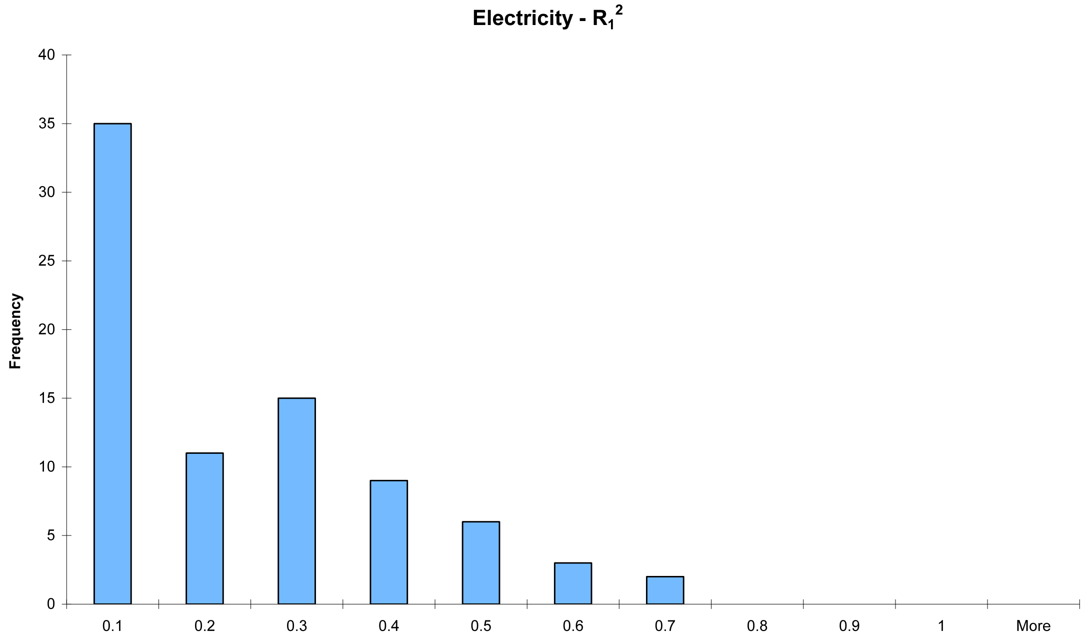


Figure 41. Histogram of electricity R_1^2 regression coefficient

The low values of the correlation coefficients (R_1^2 and R_2^2) between electricity use and temperature, and the high number of non-significant regression slopes can be partially explained by the fact that there are few Leicester City Council buildings with air-conditioning systems. Therefore a strong relationship between electricity consumption and outside temperature was not expected to occur for most of the buildings. However, there are other factors that affect electricity and temperature relationship that need to be considered. Non-domestic buildings have a significant number of end-uses for electricity, which can mask the impact of air-conditioning in the primary meter electricity data. A complete analysis of relationships that affect the electricity consumption patterns would require additional information. For instance, to identify the relationship with temperature it would probably be necessary to have sub-metering energy use data for the air conditioning systems. Other relationships with electricity consumption could be found by using multiple regression models, applied to humidity and solar radiation data, as presented in (ASHRAE, 2001).

Since only primary meter electricity and outside temperature data was available, IMT model parameters were only significant for a limited set of buildings. Therefore it was considered that the analysis of the relationship between primary meter daily electricity use and mean daily temperature was not sufficiently powerful to produce meaningful indicators.

7.1.2. Gas analysis

Table 15 presents the summary of results for load shape indicators calculated for primary meter half-hourly gas data. The full results are presented in Table 16. Gas and electricity consumption load shape indicators results are similar, in terms of the mean, maximum and minimum values. However, gas load shape indices have generally higher standard deviations.

Table 15. Summary of gas load demand shape indices

Summary Statistics	α_{D1}	α_{D2}	α_{D3}	α_{D4}	α_{D5}	α_{D6}	α_{D7}	α_{D8}	α_{D9}	α_{W1}	α_{W2}	α_{W3}
Mean	0.60	0.44	0.77	0.71	0.91	0.54	0.68	0.78	0.95	0.61	0.45	0.83
Median	0.63	0.43	0.81	0.82	0.97	0.64	0.77	0.83	0.97	0.64	0.49	0.97
Standard Deviation	0.23	0.34	0.16	0.28	0.12	0.36	0.32	0.30	0.17	0.23	0.34	0.28
Minimum	0.16	0.00	0.31	0.00	0.45	0.00	0.01	0.00	0.09	0.16	0.00	0.00
Maximum	0.96	0.94	0.97	0.97	1.00	1.00	1.29	1.36	1.19	0.97	0.95	1.07
Count	81.00	81.00	81.00	81.00	81.00	81.00	81.00	81.00	81.00	81.00	81.00	81.00

From Table 15 it is possible to observe that mean values vary from 0.44 (α_{D2}) to 0.91 (α_{D5}). The standard deviation varies from 0.12 (α_{D5}) to 0.36 (α_{D6}), in some cases very close to the means. Results range between maximum and minimum values is quite large for most indicators, and several indicators have minimum values near zero. For example α_{D1}, which represents the load factor, has relatively low standard deviation of 0.23 when compared to the mean 0.60. However, it has a high dispersion, the minimum value is 0.16 and the maximum value 0.96. The histogram presented in Figure 42 can help in the interpretation of the results for this indicator. Although α_{D1} has more than 25 values above 0.70, a wide dispersion is noticeable.

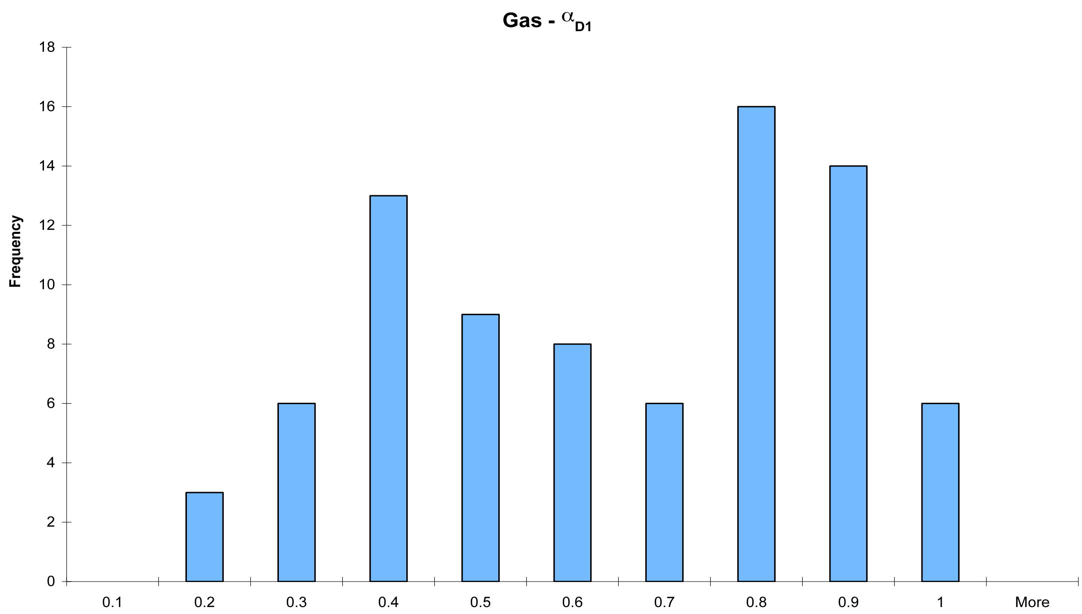


Figure 42. Histogram of gas α_{D1} load shape indicator

Table 16. Gas load demand shape indices

Meters	α_{D1}	α_{D2}	α_{D3}	α_{D4}	α_{D5}	α_{D6}	α_{D7}	α_{D8}	α_{D9}	α_{W1}	α_{W2}	α_{W3}
16 New Walk Gas	0.35	0.07	0.56	0.59	0.91	0.08	0.38	1.09	0.82	0.35	0.10	0.10
308 Melton Rd Gas	0.84	0.83	0.93	0.94	0.99	0.80	0.86	0.92	1.01	0.81	0.83	0.96
47 New Walk Gas	0.23	0.02	0.82	0.89	0.45	0.02	0.18	0.61	0.98	0.27	0.02	0.66
Abbey House EPH Gas	0.63	0.36	0.77	0.77	0.87	0.44	0.91	0.98	0.93	0.62	0.37	0.95
Arbor House EPH Gas	0.67	0.04	0.84	0.84	0.96	0.04	0.67	0.72	0.98	0.68	0.15	1.03
Ash Field School Gas	0.78	0.79	0.85	0.82	1.00	0.88	0.92	1.06	0.98	0.80	0.84	0.67
Attenborough House Gas	0.67	0.69	0.76	0.83	0.95	0.77	0.80	0.82	0.91	0.68	0.69	1.01
Aylestone Les Main Gas	0.76	0.54	0.95	0.96	0.94	0.48	0.68	0.68	1.00	0.81	0.58	0.99
Aylestone Library Gas	0.56	0.59	0.77	0.67	1.00	0.64	0.70	0.71	0.81	0.61	0.61	1.01
Barnes Heath House Gas	0.91	0.83	0.86	0.88	1.00	1.00	1.03	1.04	0.94	0.92	0.84	1.02
Barnett Janner WAA Gas	0.77	0.57	0.86	0.93	1.00	0.56	0.78	0.77	0.96	0.77	0.58	1.01
Beatty Ave B Gas	0.72	0.41	0.88	0.95	0.91	0.39	0.71	0.70	0.97	0.75	0.41	1.00
Beaumanor Hostel Gas	0.70	0.21	0.88	0.91	0.86	0.21	0.82	0.80	0.97	0.70	0.20	1.01
Home Farm AHO Main Gas	0.81	0.84	0.87	0.90	1.00	0.87	0.94	0.97	0.98	0.84	0.87	1.06
Coss Fam Centre Gas	0.18	0.04	0.42	0.03	1.00	0.64	0.05	1.00	0.82	0.19	0.05	0.03
Belgrave Library Gas	0.52	0.08	0.66	0.69	0.78	0.12	1.29	1.36	0.92	0.53	0.10	0.61
Belgrave Neigh. Cent Gas	0.44	0.02	0.60	0.59	0.92	0.03	0.46	0.50	0.95	0.44	0.02	0.87
Bowder House WAA Gas	0.72	0.65	0.86	0.93	0.90	0.66	0.88	0.90	0.94	0.71	0.66	1.00
Braunstone Oak NC Gas	0.36	0.04	0.56	0.08	0.99	0.36	0.09	0.11	0.18	0.37	0.04	0.53
Bridges House WAA Gas	0.86	0.68	0.96	0.96	0.99	0.64	0.77	0.78	1.00	0.86	0.68	1.01
Butterwick Gas	0.51	0.32	0.75	0.86	0.71	0.36	0.77	0.77	0.94	0.51	0.32	1.01
Catherine Jnr School Gas	0.16	0.00	0.31	0.00	1.00	0.00	0.01	0.00	0.09	0.16	0.00	0.00
Central Library Gas	0.74	0.73	0.87	0.91	0.68	1.00	1.13	1.10	0.96	0.78	0.77	0.75
Reference Library Gas	0.40	0.03	0.71	0.76	1.00	0.02	0.23	0.32	0.96	0.39	0.04	0.51
Charnwood AHO Main Gas	0.37	0.18	0.62	0.11	0.98	1.00	0.35	0.34	0.98	0.37	0.16	0.96
Coleman Neigh Centre Gas	0.48	0.72	0.78	0.85	0.72	0.73	0.78	0.83	0.95	0.53	0.73	0.97
Coss Pool Main Gas	0.86	0.85	0.94	0.88	0.96	0.92	0.92	0.95	1.03	0.90	0.87	0.98
Cromwell House WAA Gas	0.89	0.89	0.93	0.95	1.00	0.89	0.93	0.94	0.97	0.89	0.89	1.01
Dudley House WAA Gas	0.68	0.43	0.88	0.94	0.83	0.42	0.76	0.75	0.96	0.71	0.44	1.01
Elizabeth House EPH Gas	0.82	0.79	0.87	0.87	1.00	0.85	0.94	0.96	0.97	0.82	0.79	1.00
Energy Office Gas	0.29	0.15	0.67	0.75	0.69	0.12	0.26	0.42	0.89	0.34	0.18	0.67
Evington Library Gas	0.43	0.14	0.82	0.77	1.00	0.09	0.15	0.16	1.06	0.44	0.13	0.94
Fred.Thorpe WAA Gas	0.63	0.51	0.78	0.94	0.91	0.48	0.76	0.77	0.97	0.64	0.52	1.01
Gumbrill House WAA Gas	0.86	0.78	0.91	0.95	1.00	0.78	0.91	0.91	0.97	0.87	0.78	1.01
Heatherbrook Sch Gas	0.36	0.07	0.67	0.18	0.94	0.22	0.16	0.52	1.05	0.37	0.17	0.73
Helena Roberts WAA Gas	0.87	0.90	0.92	0.95	0.98	0.91	0.93	0.94	0.98	0.89	0.90	1.01
Herrick Lodge EPH Gas	0.54	0.36	0.81	0.60	1.00	0.40	0.48	0.51	1.16	0.56	0.36	0.90
Home Improvement Agy Gas	0.90	0.88	0.88	0.91	1.00	1.00	1.05	1.09	0.98	0.91	0.88	0.98
Humberstone AHO Main Gas	0.44	0.07	0.76	0.78	0.76	0.07	0.65	0.65	0.99	0.44	0.07	1.02
Jackson House WAA Gas	0.89	0.83	0.93	0.92	1.00	0.87	0.90	0.89	0.96	0.90	0.84	1.01
Judgemeadow CC Gas	0.50	0.02	0.65	0.76	0.94	0.02	0.57	0.40	0.88	0.49	0.05	0.43
Lansdowne Neigh Cent Gas	0.71	0.84	0.84	0.71	1.00	1.00	0.84	0.77	1.14	0.66	0.81	1.00
Lansdowne Pre School Gas	0.52	0.35	0.86	0.55	1.00	0.39	0.42	1.00	1.09	0.54	0.42	0.49
Lough Rd Hostel Gas	0.95	0.94	0.97	0.97	1.00	0.96	0.98	0.99	1.01	0.95	0.95	1.00
31 Lower Hastings St Gas	0.48	0.10	0.54	0.13	0.96	0.72	0.50	0.51	0.30	0.48	0.10	0.97
33 Lower Hastings St Gas	0.94	0.93	0.96	0.97	0.99	0.94	0.98	0.98	1.00	0.96	0.94	1.01
Marlborough House Gas	0.31	0.01	0.67	0.70	0.79	0.01	0.16	1.25	0.92	0.32	0.02	0.12
Millgate Centre Main Gas	0.65	0.61	0.85	0.91	0.94	0.54	0.76	1.06	0.98	0.69	0.49	0.76
Nether Hall School Gas	0.48	0.07	0.77	0.08	1.00	0.57	0.46	0.47	1.10	0.49	0.05	0.91
Netherhall Childrens Gas	0.77	0.82	0.85	0.82	1.00	0.90	0.93	0.94	0.95	0.79	0.81	0.96
Netherhall Neigh Cent Gas	0.81	0.71	0.77	0.76	0.97	1.00	1.10	1.21	1.06	0.80	0.70	0.95
New College Main Gas	0.19	0.01	0.40	0.01	1.00	0.95	0.01	0.25	0.92	0.19	0.01	0.07
New Parks AHO Gas	0.55	0.59	0.73	0.59	0.90	0.84	0.77	0.84	0.94	0.56	0.63	0.95
New Parks Les Gas	0.77	0.50	0.94	0.96	0.97	0.43	0.62	0.61	1.00	0.77	0.49	1.00
New Walk B Block Gas	0.36	0.10	0.72	0.73	0.82	0.08	0.25	0.58	0.96	0.34	0.13	0.49
New Walk Museum Gas	0.83	0.75	0.75	0.87	0.96	1.00	1.14	1.15	0.91	0.83	0.74	1.03
Norfolk House WAA Gas	0.72	0.71	0.87	0.94	0.87	0.72	0.85	0.83	0.98	0.74	0.72	1.00
Nuffield House EPH Gas	0.77	0.80	0.92	0.90	0.80	0.93	1.06	1.08	1.01	0.76	0.80	1.00
Phoenix House Gas	0.40	0.12	0.74	0.66	0.74	0.13	0.63	0.96	0.97	0.40	0.18	0.53
Pollard House WAA Gas	0.84	0.85	0.89	0.95	0.99	0.84	0.89	0.90	0.97	0.84	0.85	1.02
Preston Lodge EPH Gas	0.76	0.87	0.83	0.86	1.00	0.92	0.89	0.90	0.96	0.76	0.88	1.00
Rowsley St AHO Gas	0.26	0.08	0.56	0.61	0.69	0.09	0.16	0.15	0.98	0.30	0.09	0.92
Rupert Hse WAA Gas	0.80	0.68	0.89	0.96	0.99	0.64	0.80	0.82	0.98	0.81	0.70	1.01
Saffron AHO Gas	0.38	0.16	0.64	0.39	0.65	0.37	0.96	1.13	1.08	0.36	0.17	0.91
Scraptoft Valley Prim. Gas	0.22	0.00	0.62	0.01	0.50	0.00	0.49	0.79	1.03	0.25	0.05	0.68
Sth Braunstone AHO Gas	0.83	0.89	0.90	0.82	1.00	1.00	0.94	1.00	1.03	0.86	0.91	0.96
Southfields Library Gas	0.41	0.10	0.72	0.80	0.74	0.10	0.55	0.71	0.94	0.39	0.12	0.50
Spence St Hall Main Gas	0.24	0.07	0.43	0.52	1.00	0.07	0.23	0.46	1.15	0.19	0.17	0.90
Spence St Pool Gas	0.84	0.71	0.95	0.96	0.97	0.68	0.78	0.77	0.97	0.85	0.70	0.98
St Marks AHO Main Gas	0.96	0.94	0.94	0.96	1.00	1.00	1.02	1.00	0.99	0.97	0.95	1.03
St Saviours NC Gas	0.38	0.06	0.69	0.50	1.00	0.07	0.08	0.11	1.10	0.43	0.07	0.94
Tatlow Rd Comm Home Gas	0.78	0.88	0.84	0.89	1.00	0.93	0.94	0.97	1.01	0.85	0.90	1.01
The City Gallery Gas	0.23	0.00	0.47	0.54	1.00	0.00	0.04	0.08	0.77	0.23	0.01	0.57
Tudor Centre Gas	0.60	0.54	0.73	0.61	0.94	0.78	0.76	0.81	0.99	0.60	0.55	1.02
Thurnby Lodge Primary Gas	0.38	0.05	0.56	0.04	0.99	1.00	0.54	1.29	1.19	0.39	0.08	0.20
Thurncourt EPH Gas	0.73	0.36	0.92	0.93	0.81	0.38	0.91	0.94	0.97	0.72	0.37	1.00
Town Hall Gas	0.38	0.22	0.73	0.65	0.81	0.23	0.33	0.50	1.01	0.38	0.23	0.56
38 Upper Titchbourne Gas	0.92	0.90	0.91	0.94	0.97	1.00	1.05	1.06	0.97	0.92	0.89	1.01
Welford House Gas	0.35	0.01	0.61	0.79	0.61	0.01	1.00	0.91	0.86	0.34	0.01	0.59
Westcotes Library Gas	0.31	0.05	0.37	0.55	0.88	0.08	0.89	0.84	0.84	0.32	0.04	1.07
Whitehall Sch Main Gas	0.47	0.39	0.70	0.39	0.86	0.79	0.71	1.02	1.09	0.51	0.50	0.53

The following Table 17 presents the summary statistics for gas IMT model parameters, which are presented in full in Table 18.

Table 17. Summary of gas IMT model parameters - weekdays

Summary Statistics	c	b_1	b_2	b_3	$RMSE_1$	$RMSE_2$	R_1^2	R_2^2
Mean	380.88	-89.05	29.37	18.53	269.70	44.86	0.71	0.28
Median	126.31	-55.52	-0.20	18.46	151.94	19.43	0.77	0.13
Standard Deviation	550.52	103.23	190.49	4.89	330.27	92.30	0.20	0.32
Minimum	-986.20	-529.51	-68.91	0.46	0.72	0.00	0.01	0.00
Maximum	2476.09	5.59	1500.16	44.28	1523.61	638.18	0.95	1.00
Count	81.00	81.00	81.00	81.00	81.00	81.00	81.00	81.00

Interestingly, and in contrast to what was found for electricity, outside temperature and gas consumption are strongly related and can be described by the IMT model.

Figure 43 presents the histogram for the coefficient of determination, R_1^2, for the linear regression between daily mean outside temperature and total daily gas consumption, for values below the change-point temperature b_3. Apparently, in about 67 datasets (in a total of 81) with R_1^2 above 0.60, a linear model can describe the relation between daily gas consumption and outside temperature. Note that p-values for the slope of the first regression line, b_1, are above the level of significance for only 2 datasets. Therefore, R_1^2 values presented in table and histogram can be said to be meaningful to all datasets, except for:

- Catherine Jnr School Gas, and
- New College Main Gas.

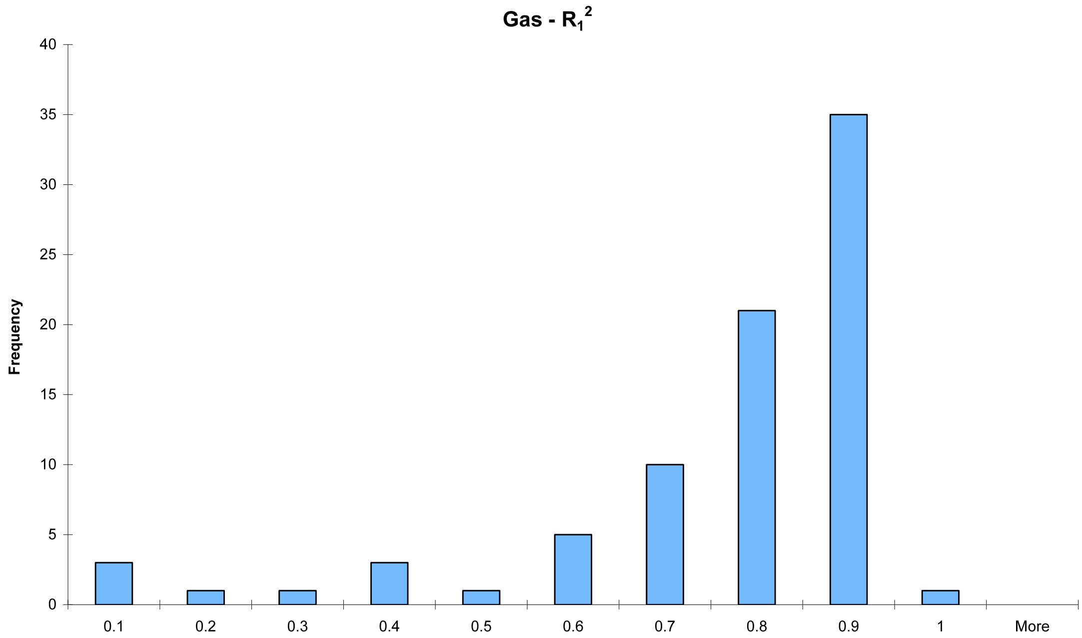


Figure 43. Histogram of gas R_1^2 regression

From the results for the second regression line (for temperatures above b_3) it is possible to conclude that b_2 is not statistically significant different from zero for about 73 meters (p-value above 0.05). In other words, the parameter b_2 is not different from zero for most of the gas energy use IMT models (73 out of 81). Therefore computed results for b_2 were not able to be used as parameters for most of the gas consumption datasets under study.

This implies that a three-parameter heating model would be sufficient for most of the datasets. Note that the difference between models is the value of b_2. In the 3-parameter model is b_2 is zero, and in the four-parameter model b_2 is the slope of the regression line for points above the change-point temperature b_3.

Table 18. Gas IMT model parameters - weekdays

Meters	c	b_1	b_2	b_3	$RMSE_1$	$RMSE_2$	R_1^2	R_2^2	p-value(b_1)	p-value(b_2)
16 New Walk Gas	106.79	-107.64	0.44	17.01	426.23	9.30	0.67	0.00	0.00	0.90
308 Melton Rd Gas	535.02	-162.42	815.10	17.93	424.79	209.96	0.70	0.81	0.00	0.29
47 New Walk Gas	38.12	-17.18	3.49	18.88	44.14	12.11	0.82	0.15	0.00	0.45
Abbey House EPH Gas	776.28	-84.92	-22.22	18.75	254.16	22.58	0.79	0.67	0.00	0.05
Arbor House EPH Gas	823.33	-86.41	-8.34	19.48	210.11	49.85	0.85	0.06	0.00	0.65
Ash Field School Gas	740.79	-175.85	42.42	20.80	437.62	189.10	0.83	0.10	0.00	0.60
Attenborough House Gas	-986.20	-36.88	-41.69	44.28	95.61	8.45	0.75	0.89	0.00	0.02
Aylestone Les Main Gas	2074.99	-295.87	-68.91	13.64	743.37	442.59	0.74	0.10	0.00	0.02
Aylestone Library Gas	17.77	-14.71	-1.06	17.31	0.72	0.58	0.72	0.01	0.00	0.65
Barnes Heath House Gas	577.58	-54.24	-17.14	17.18	209.13	1.10	0.69	1.00	0.00	0.04
Barnett Janner WAA Gas	365.57	-69.87	-11.90	18.82	139.45	24.52	0.89	0.33	0.00	0.23
Beatty Ave B Gas	1437.13	-146.97	-13.24	18.68	295.61	62.49	0.89	0.09	0.00	0.57
Beaumanor Hostel Gas	399.48	-46.12	3.01	19.08	132.08	3.96	0.80	0.41	0.00	0.56
Home Farm AHO Main Gas	4.59	-14.75	8.28	20.20	50.78	0.00	0.61	1.00	0.00	0.00
Coss Fam Centre Gas	-6.11	-0.82	-1.40	33.03	8.63	3.15	0.22	0.30	0.00	0.26
Belgrave Library Gas	13.06	-36.99	-0.23	16.96	173.33	0.22	0.60	0.69	0.00	0.04
Belgrave Neigh. Cent Gas	202.93	-95.35	0.75	18.65	234.17	20.92	0.84	0.00	0.00	0.92
Bowder House WAA Gas	669.05	-47.60	-13.51	17.65	180.22	29.29	0.69	0.31	0.00	0.25
Braunstone Oak NC Gas	-42.55	-41.32	30.35	19.91	8.80	6.84	0.72	0.33	0.00	0.00
Bridges House WAA Gas	107.33	-57.90	6.61	19.50	141.64	30.13	0.84	0.09	0.00	0.56
Butterwick Gas	857.28	-131.35	-53.38	18.42	257.86	77.60	0.89	0.50	0.00	0.12
Catherine Jnr School Gas	73.43	-0.32	0.02	18.19	13.72	6.50	0.01	0.00	0.10	1.00
Central Library Gas	935.24	-61.89	-58.82	0.46	225.76	58.45	0.52	0.55	0.00	0.15
Reference Library Gas	22.21	-107.48	0.12	15.83	290.58	1.50	0.79	0.02	0.00	0.48
Charnwood AHO Main Gas	0.47	-7.15	3.25	18.75	30.96	10.34	0.64	0.17	0.00	0.41
Coleman Neigh Centre Gas	51.90	-28.34	-5.67	19.13	89.23	12.72	0.77	0.30	0.00	0.26
Coss Pool Main Gas	1507.66	-208.94	52.04	20.55	789.00	638.18	0.64	0.02	0.00	0.47
Cromwell House WAA Gas	637.19	-70.89	-12.22	17.29	177.26	7.44	0.84	0.85	0.00	0.01
Dudley House WAA Gas	458.44	-65.45	-4.63	18.66	138.82	40.05	0.88	0.03	0.00	0.75
Elizabeth House EPH Gas	1049.18	-70.25	11.10	18.46	237.46	39.74	0.74	0.14	0.00	0.46
Energy Office Gas	3.07	-20.59	-0.20	17.71	47.02	0.46	0.86	0.29	0.00	0.27
Evington Library Gas	-27.32	-146.50	159.26	18.10	486.34	37.24	0.52	0.94	0.00	0.15
Fred.Thorpe WAA Gas	440.24	-55.52	-0.60	18.57	107.36	19.43	0.90	0.00	0.00	0.93
Gumbrill House WAA Gas	474.25	-72.56	-7.58	18.04	147.40	19.56	0.89	0.24	0.00	0.32
Heatherbrook Sch Gas	286.15	-52.94	7.74	18.39	308.20	46.42	0.51	0.06	0.00	0.65
Helena Roberts WAA Gas	653.74	-66.66	-10.57	17.39	160.06	10.93	0.85	0.67	0.00	0.05
Herrick Lodge EPH Gas	876.65	5.59	-17.81	18.83	110.80	45.29	0.08	0.25	0.00	0.32
Home Improvement Agy Gas	17.05	-10.88	-1.09	18.10	28.84	4.06	0.82	0.13	0.00	0.48
Humberstone AHO Main Gas	18.18	-19.48	-0.15	17.98	46.17	1.84	0.85	0.01	0.00	0.83
Jackson House WAA Gas	402.00	-61.37	-4.21	18.51	150.42	28.18	0.84	0.05	0.00	0.69
Judgemeadow CC Gas	1560.98	-427.30	1500.16	15.36	1523.61	0.00	0.49	1.00	0.00	0.00
Lansdowne Neigh Cent Gas	64.07	-20.81	-4.06	18.49	153.65	12.95	0.36	0.17	0.00	0.41
Lansdowne Pre School Gas	20.95	-42.10	3.08	18.53	107.33	37.57	0.83	0.01	0.00	0.82
Lough Rd Hostel Gas	199.75	-41.00	-6.77	19.20	82.48	18.65	0.89	0.22	0.00	0.35
31 Lower Hastings St Gas	40.33	-12.64	-3.13	18.92	37.95	7.61	0.78	0.26	0.00	0.30
33 Lower Hastings St Gas	115.20	-23.78	2.34	18.93	73.17	23.20	0.77	0.02	0.00	0.78
Marlborough House Gas	16.01	-15.19	0.00	16.47	35.73	5.45	0.81	0.00	0.00	1.00
Millgate Centre Main Gas	681.68	-334.00	31.64	18.81	1061.39	127.46	0.76	0.12	0.00	0.51
Nether Hall School Gas	259.52	-126.78	17.55	19.06	397.36	95.48	0.77	0.07	0.00	0.62
Netherhall Childrens Gas	126.31	-23.75	-5.60	16.52	91.52	23.39	0.61	0.14	0.00	0.04
Netherhall Neigh Cent Gas	14.09	-40.94	3.90	18.93	84.10	15.43	0.88	0.12	0.00	0.50
New College Main Gas	133.55	-0.62	-0.07	0.46	32.90	5.71	0.01	0.00	0.19	0.98
New Parks AHO Gas	-258.34	-20.19	-24.51	31.18	62.26	2.68	0.63	0.98	0.00	0.09
New Parks Les Gas	2476.09	-151.47	-6.11	21.77	430.51	145.75	0.80	0.00	0.00	0.91
New Walk B Block Gas	213.03	-529.51	-0.37	18.19	1213.05	13.95	0.86	0.00	0.00	0.94
New Walk Museum Gas	70.33	-246.61	2.41	17.62	590.00	24.20	0.84	0.02	0.00	0.79
Norfolk House WAA Gas	503.99	-67.31	8.36	18.95	174.15	100.27	0.83	0.01	0.00	0.82
Nuffield House EPH Gas	567.86	-98.65	6.79	21.84	208.23	65.71	0.88	0.02	0.00	0.78
Phoenix House Gas	60.94	-98.46	-2.50	18.04	275.20	8.98	0.81	0.14	0.00	0.46
Pollard House WAA Gas	721.52	-51.35	-16.33	17.08	106.31	28.54	0.88	0.41	0.00	0.17
Preston Lodge EPH Gas	1254.34	-114.74	-34.41	18.73	389.91	27.73	0.74	0.77	0.00	0.02
Rowsley St AHO Gas	6.88	-8.64	-0.26	18.30	23.04	4.23	0.82	0.01	0.00	0.87
Rupert Hse WAA Gas	588.63	-74.28	-4.64	19.02	205.33	28.03	0.81	0.05	0.00	0.65
Saffron AHO Gas	38.18	-35.54	2.84	17.68	107.68	21.67	0.78	0.04	0.00	0.72
Scraptoft Valley Prim. Gas	28.25	-162.68	5.29	17.94	374.40	2.62	0.84	0.94	0.00	0.16
Sth Braunstone AHO Gas	60.55	-14.06	-1.31	16.72	41.05	0.49	0.72	0.96	0.00	0.12
Southfields Library Gas	23.37	-108.07	0.11	15.92	338.69	1.32	0.72	0.02	0.00	0.45
Spence St Hall Main Gas	75.32	-28.03	74.36	10.98	151.94	84.28	0.17	0.33	0.00	0.14
Spence St Pool Gas	1760.64	-82.10	-20.64	23.06	643.76	68.27	0.35	0.16	0.00	0.43
St Marks AHO Main Gas	-1.78	-16.02	24.88	21.25	54.27	22.70	0.74	0.72	0.00	0.03
St Saviours NC Gas	11.95	-7.93	9.71	21.59	36.33	18.63	0.61	0.37	0.00	0.20
Tatlow Rd Comm Home Gas	119.25	-16.52	-2.02	19.19	44.29	9.20	0.82	0.09	0.00	0.56
The City Gallery Gas	108.82	-18.44	-1.83	17.22	50.11	5.83	0.81	0.17	0.00	0.41
Tudor Centre Gas	48.81	-25.86	2.43	17.17	182.89	9.01	0.40	0.13	0.00	0.48
Thurnby Lodge Primary Gas	232.43	-319.64	10.20	18.17	1504.39	49.46	0.58	0.09	0.00	0.63
Thurncourt EPH Gas	644.91	-81.09	-7.57	19.70	108.21	28.85	0.95	0.13	0.00	0.49
Town Hall Gas	211.72	-379.24	0.84	18.17	1187.48	27.34	0.77	0.00	0.00	0.93
38 Upper Titchbourne Gas	19.68	-25.89	-2.18	18.69	53.83	4.56	0.88	0.09	0.00	0.71
Welford House Gas	42.37	-139.68	15.14	16.31	401.19	0.00	0.70	1.00	0.00	0.00
Westcotes Library Gas	4.94	-37.06	1.15	17.52	120.39	8.46	0.75	0.04	0.00	0.71
Whitehall Sch Main Gas	1392.36	-298.42	32.75	18.21	1032.12	214.77	0.73	0.05	0.00	0.68

From the table above it was also possible to identify other difficulties in the application of IMT model to available data. For about 6 datasets the parameter c was found to be negative, however negative non-weather related gas usage is possible if there are other sources of heating supply to the buildings, for instance district heating or electric heating with night storage. Additionally, 2 datasets were found to have an excessive high parameter c when compared with total energy use. These difficulties in the application of IMT model can also be related to poor control of heating systems.

The datasets that resulted in negative values for parameter c were:

- Attenborough House Gas
- Coss Fam Centre Gas
- Braunstone Oak NC Gas
- Evington Library Gas
- New Parks AHO Gas
- St Marks AHO Main Gas

The datasets for which an excessively high non-weather related gas use was found were:

- Central Library Gas
- Herrick Lodge EPH Gas

This excessively high non-weather related gas use was only found because of the indicators normalisation. For these two buildings it was found that calculated non-weather related energy use was above the total annual consumption (parameter c_n presented below was above 1.00), which is not possible in reality.

The parameter c, the non-weather related energy use, is expressed in units of energy consumption – kWh, b_1 is the slope of the regression lines below change-point temperature, and it is expressed in kWh/ºC. The change-point temperature b_3, is expressed in ºC.

These parameters are directly related to the building total energy consumption, and consequently this is related to building size, thermal characteristics, occupancy patterns, etc. Therefore it is not possible to compare different datasets without normalising results first.

As stated before, normalisation is necessary to provide a meaningful comparison between datasets and consequently between buildings. Usually, non-domestic buildings annual energy consumption is normalised by floor area. As presented before the use of NPI is suggested in most of building energy management publications, starting by government guidance for local authorities, the Carbon Trust Energy Consumption Guide for Energy use in Local Authority Buildings (Carbon Trust, 2004).

Floor area was not available for all the building under analysis. Therefore it was not possible to use floor area as a normalisation factor. Instead annual energy consumption was selected for the normalisation of regression coefficients. Total annual energy consumption is easily calculated from available primary meter half-hourly data, and it is directly related to building size and occupancy. The normalisation of c and b_1 parameters was computed using the following equations.

$$c_n = \frac{c \times 5 \times 52}{E_{weekdays}}$$

Equation 22. Normalisation of non-weather related gas use – c_n

$$b_{1n} = \frac{b_1 \times 1000}{E_{weekdays}}$$

Equation 23. Normalisation of non-weather related gas use – b_{1n}

The parameter c represents the non-weather gas use on weekdays. The constant 5x52 represents the number of weekdays in a year. The resulting c_n is the ratio between annual non-weather related gas use and total annual gas consumption on weekdays $E_{weekdays}$. Similarly, the total annual gas usage on weekdays was also used for the normalised indicator b_{1n}. The normalisation of c parameter using annual energy consumption produces a quite meaningful parameter, c_n, which is the percentage of energy used for water heating, cooking and other non-weather related uses. Nevertheless, the meaningfulness of b_1 normalisation is accurate to the extent that total annual energy consumption represents the size of the building. Further research is necessary to compare results from different possible approaches to the normalisation of b_1 parameter.

Table 19 presents the summary statistics of IMT model parameters for the 71 datasets for which the model was successfully applied. It is possible to say that IMT model resulted in the calculations of c, b1 and b3 parameter for 88% of the data (71 out of 81 datasets). The table also includes normalised indicators c_n and b_{1n}.

Table 19. New summary of gas regression coefficients calculation

Summary Statistics	c	c_n	b_1	b_{1n}	b_3	$RMSE_1$	$RMSE_2$	R_1^2	R_2^2
Mean	424.72	0.31	-97.10	-0.36	18.24	292.21	48.40	0.75	0.25
Median	202.93	0.33	-65.45	-0.33	18.42	173.33	19.56	0.80	0.12
Standard Deviation	540.91	0.22	106.66	0.17	1.73	343.07	97.88	0.14	0.31
Minimum	0.47	0.01	-529.51	-1.22	10.98	0.72	0.00	0.17	0.00
Maximum	2476.09	0.85	-7.15	-0.11	23.06	1523.61	638.18	0.95	1.00
Count	71.00	71.00	71.00	71.00	71.00	71.00	71.00	71.00	71.00

The mean value for indicator c_n is 0.31, and it can be interpreted as meaning that the non-weather related gas usage on weekdays represents about 31% of the total gas consumption for buildings under study. The following chart is the histogram for c_n indicator, for which it was possible to identify a wide variation of results. Note that for significant number of buildings, the non-weather related gas use is below 20% the total consumption.

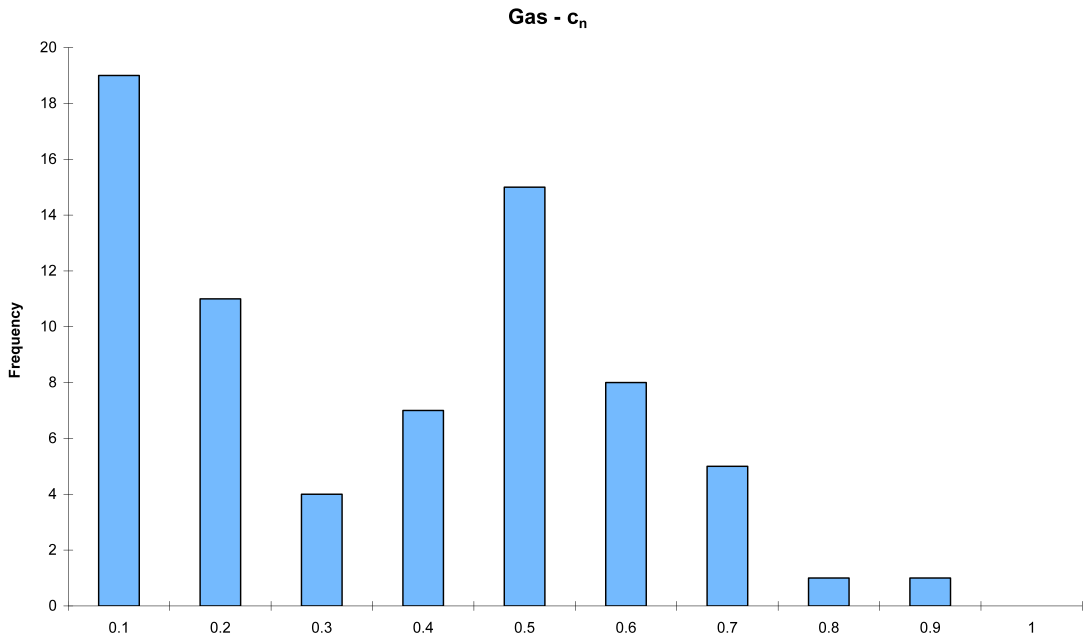


Figure 44. Histogram of gas c_n indicator results

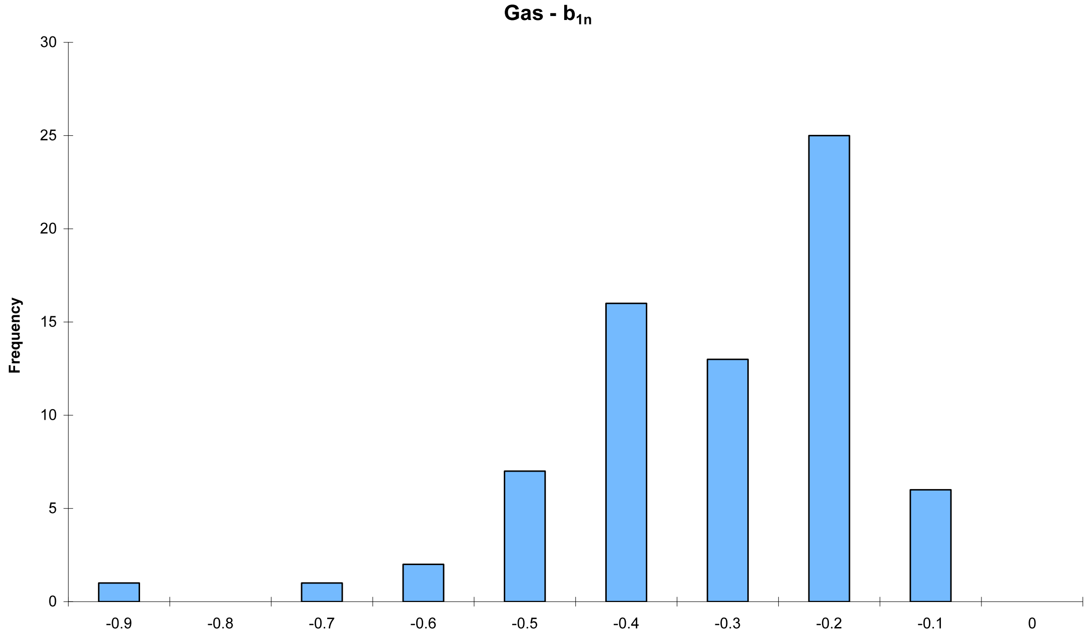


Figure 45. Histogram of gas b_{1n} indicator results

For b_{1n} it is possible to see that results are mostly centred between -0.50 and -0.20 kWh/ºC per unit of total gas use. The slope of the regression line b_1 is related to the amount of heat loss through walls, floor, roof and windows. It also accounts for the energy loss through building ventilation. The slope b_1 is also affected by internal heat gains from people and equipment. The higher the slope (in absolute terms) the more energy is used for each degree-Celsius of temperature decrease. Assuming that building size is satisfactorily modelled by total energy use, b_{1n} can be interpreted similarly to b_1. For the change-point temperature b_3 the mean value is 18.24ºC and the standard deviation 1.73ºC. Figure 46 presents the histogram plot for change-point temperatures for gas consumption datasets. More than half of the occurrences are between 17.50ºC and 20.00ºC, though there are more than 15 occurrences between 15.00ºC and 17.50ºC.

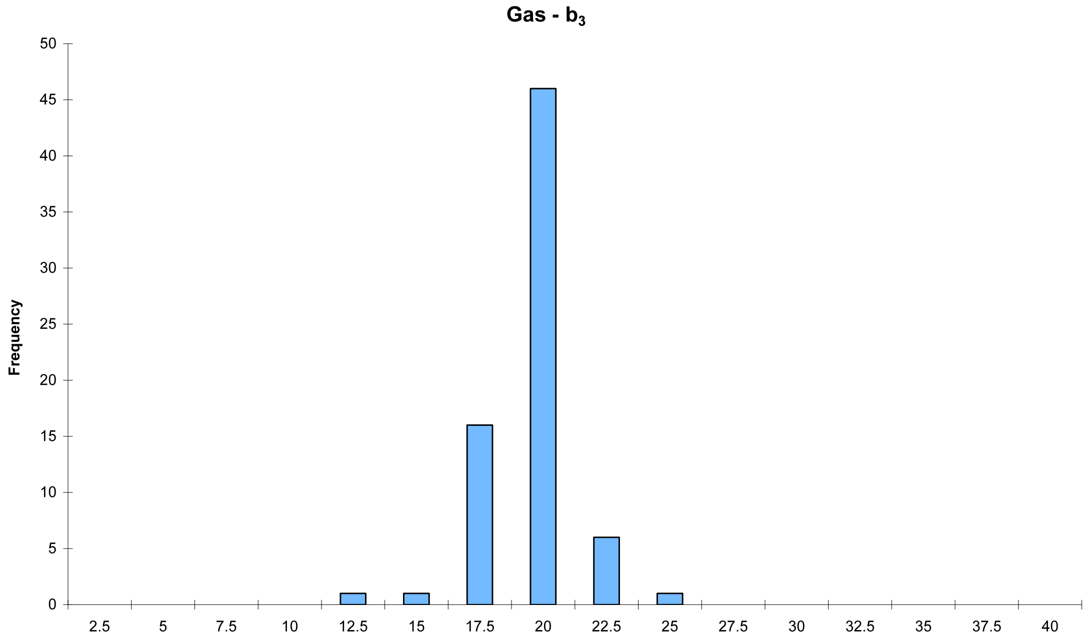


Figure 46. Histogram of gas b_3 indicator results

7.2. Selection of relevant indicators

The current work investigated the possibility of using primary meter short time series energy data, load demand shape indices and IMT model parameters to characterise energy consumption patterns of municipal buildings. The previous section presented the indicators results computed for the available building energy consumption data. This section discusses the usefulness of each indicator in characterising energy consumption profiles that can lead to the identification of potential energy saving opportunities.

From the computed indicators, it was found that α_{D1} and α_{D2} are similar to α_{W1} and α_{W2}, respectively. This was an expected result, since α_{D1} is the load factor for weekdays only, while α_{W1} is also a load factor but calculated for the week (i.e. including the weekend). Similarly, α_{D2} was calculated for weekdays and α_{W2} for the full week. A comparison between these indicators is presented in the following regression plots.

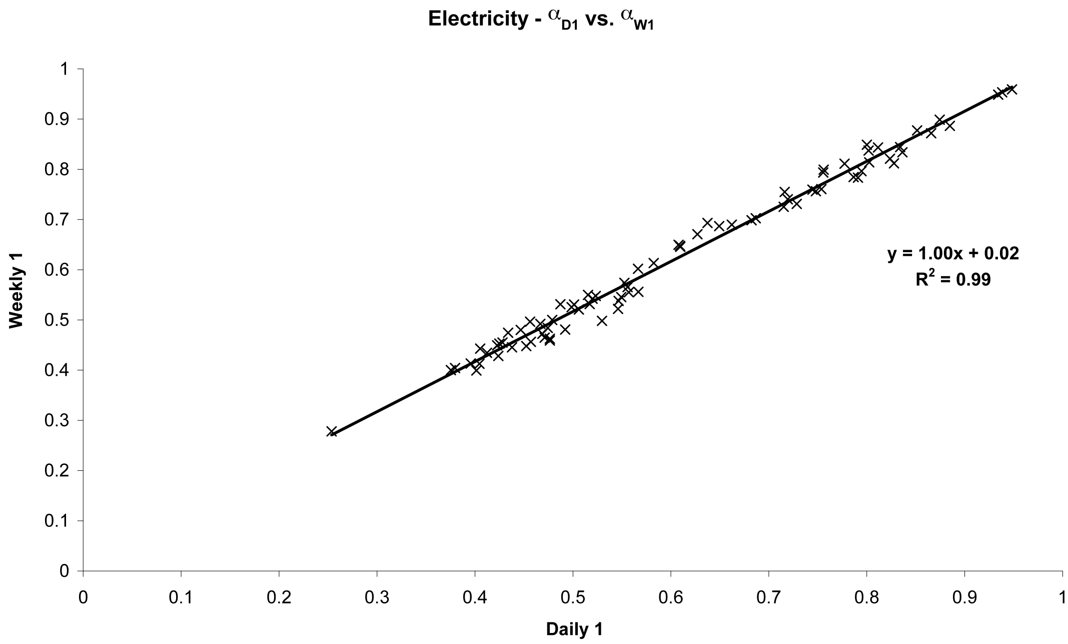


Figure 47. Comparison of electricity α_{D1} and α_{W1} load shape indicators

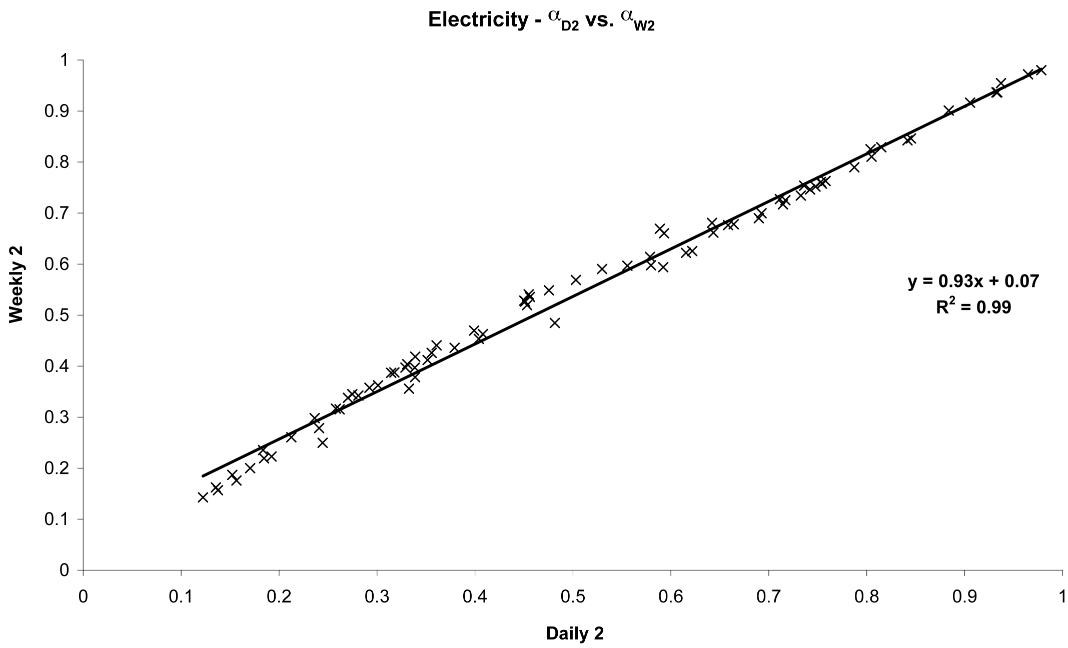


Figure 48. Comparison of electricity α_{D2} and α_{W2} load shape indicators

From Figure 47 and Figure 48 above, it is possible to conclude that α_{D1} and α_{W1} are strongly correlated. The case is identical for α_{D2} and α_{W2}. Similar results have also been found for gas data. Consequently, it can be said that α_{D1} and α_{D2} are good descriptors of α_{W1} and α_{W2}. Therefore, the analysis can focus only on α_{D1} and α_{D2}, and results extrapolated for the week long indicators α_{W1} and α_{W2}. By doing this is possible to focus the attention on a reduced set of relevant indicators.

It was also found that other indicators do not offer meaningful information for the objectives of the current work. This is the case of α_{D3}, α_{D4}, α_{D5}, α_{D6}, and α_{D9} indicators.

The α_{D3} is the load factor for working hours (8h00-18h00) on weekdays. It indicates the 'intensity' of power usage during working hours. This indicator is expected to be high, i.e. near 1.00 due to the fact that for most of the buildings peak demand occurs over the working hours. The following histogram plot presents the results of α_{D3} for electricity consumption data, and in fact most of values are above 0.80. There is only one building, the Aylestone Library, with an outlier result of α_{D3} of 0.45, mainly because the electricity use is much more intense on afternoons than on the rest of the working hours, which is not related to efficiency of operation. Therefore α_{D3} load shape indicator does not provide any relevant information to differentiate buildings consumption profiles, or even to assess efficiency of building operation and identification of potential wastage.

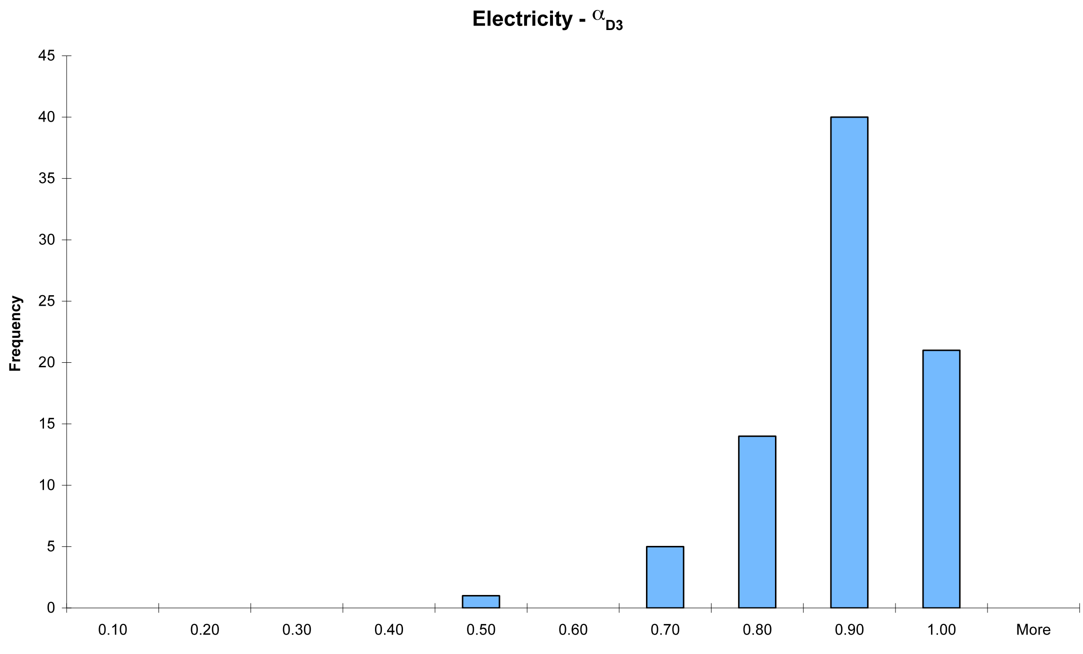


Figure 49. Histogram of electricity α_{D3} load shape indicator

A similar situation was found for α_{D4} indicator (also calculated for the working hours period between 8h00 and 18h00). This load shape indicator is a modulation coefficient that compares the minimum and the mean values during the working hours. When α_{D4} is equal to 1.00 it means that working hours are greater than 8h00 and 18h00 and that during this period energy consumption use is stable. When α_{D4} is low this might be caused by the fact that working hours are within the interval 8h00 and 18h00 (i.e. building starts being occupied after 8h00, and/or occupants leave the building before 18h00). Therefore, and without previous knowledge of the exact occupancy hours of the building, this indicator is not appropriate to identify out of hours energy use.

The α_{D6} indicator is similar to α_{D4}, but instead of calculating for the working hours period, α_{D6} compares the minimum demand during the day with the minimum on the working hours (from 8h00 to 18h00). As expected and similarly to α_{D4} the α_{D6} load demand shape indicator is not helpful if actual working hours are not known. However, other indicators, such α_{D7} and α_{D8}, are much more suitable for modelling night-time impact on weekdays and weekends, as it will be explained in detail later in this chapter.

The α_{D5} load demand shape indicator compares maximum demand over working hours with daily maximum demand. This indicator can be used to determine if the peak demand occurs on working hours, and if this is the case α_{D5} is equal to 1.00. Figure 40 presented above showed that this occurs for most of the buildings. If α_{D5} indicator is different from 1.00 the peak is attained outside the working hours, which is probably not a common feature for most of the non-domestic buildings under study, but most importantly it is not directly linked to potential energy wastage.

The α_{D9} load shape indicator assesses energy lunchtime impact on weekdays. This indicator is calculated by dividing the mean demand over lunchtime (defined as the period between 12h00 and 14h00) by the mean demand over the working-hours (8h00 to 18h00). It was expected that during lunchtime power consumption would be reduced in most of the buildings. However, and as presented in the histogram of Figure 50 this was not the case. The mean electricity consumption over lunchtime is higher than the mean demand over working hours. The α_{D9} calculated for electricity is above 1.00 for about 64 buildings (out of 81 buildings). This can be caused by several reasons, related or not with efficient occupant behaviour. The explanation could lie in the fact that most of these buildings are open to the public, so probably there are no lunchtime breaks or these are very short. The increase in consumption could lie on the fact that people bring packed lunches and use microwaves, kettles, and do not turn-off office equipment, causing the additional consumption that occurs from 12h00 and 14h00.

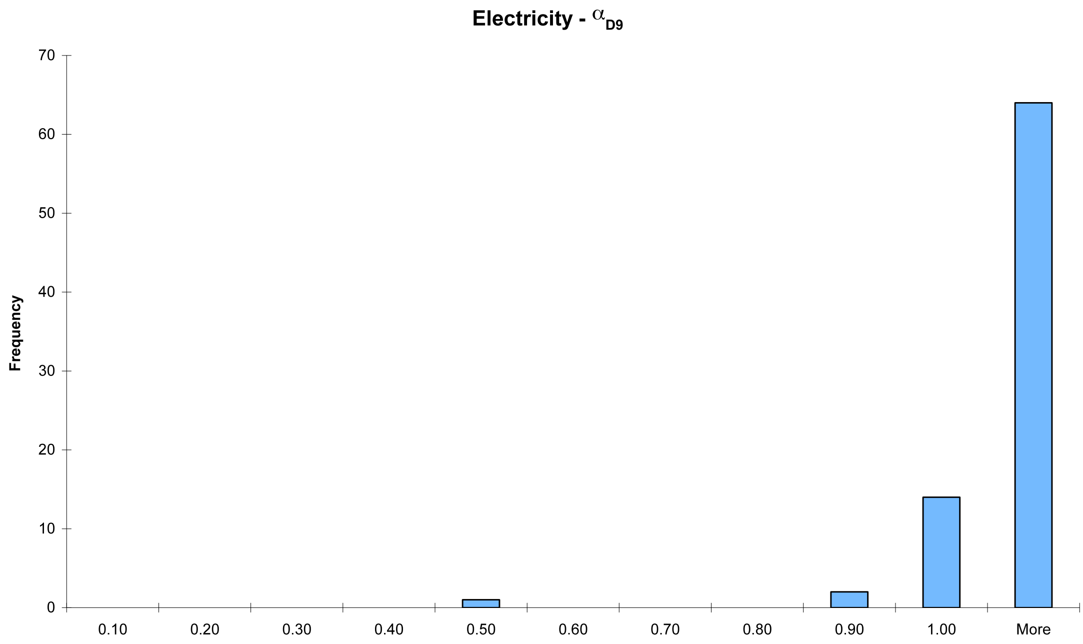


Figure 50. Histogram of electricity α_{D9} load shape indicator

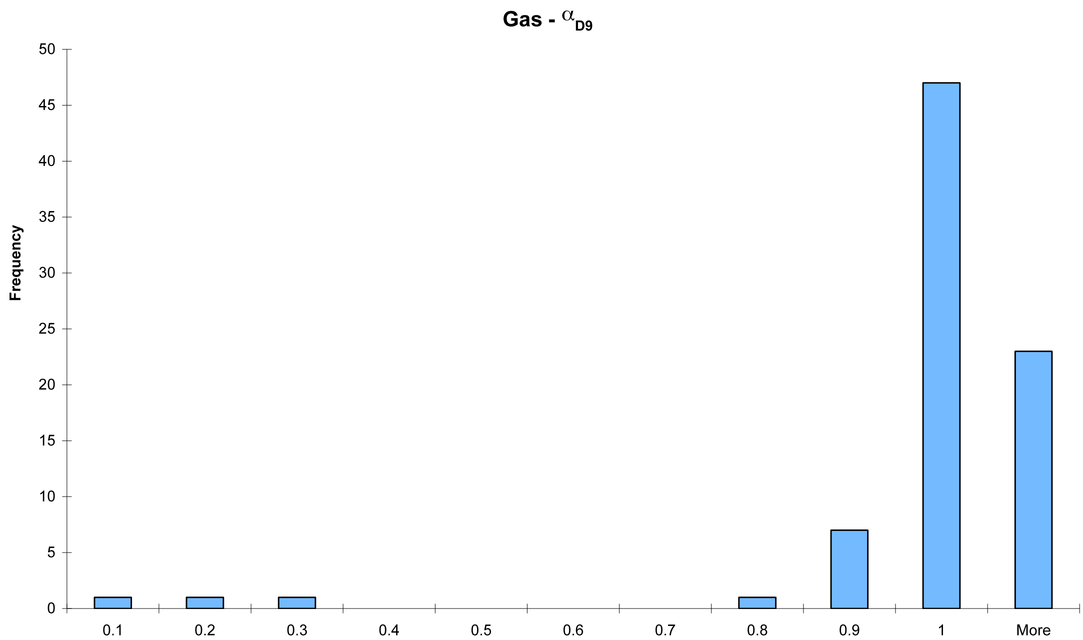


Figure 51. Histogram of gas α_{D9} load shape indicator

For gas consumption data presented in Figure 51 the results were similar, and for most of the building there was not a decrease in gas usage over lunchtime. The fact that lunchtime energy use, modelled by α_{D9}, is high or equal to the energy use in working hours is a very interesting finding. Since this is gas consumption it might be caused by the preparation of meals, i.e. cooking and hot water, at least in some buildings, such as schools, homes and hostels.

7.3. Chapter summary

Considering the analysis of electricity and gas data results using descriptive statistics it was possible to infer on the usefulness of the indicators to identify energy consumption profiles characteristics that could be related to potential energy wastage.

IMT parameters were found not to be appropriate to model electricity use. The correlation between electricity and outside temperature in Leicester buildings was found to be weak. Conversely, IMT model was suited to model gas consumption. However, the four-parameter model used produced a b_2 indicator that was found not be statistically significant different from zero for most of the buildings under study.

Load demand profile shape indicators were computed for both gas and electricity. For different reasons, some indicators were not considered to be helpful in detecting potential wastage. This was the case of indicators α_{D3}, α_{D4} and α_{D6}. The α_{D5} provide similar results for nearly all the buildings, which did not contributed to the objective in hand. And from the analysis of α_{D9} it was found that lunchtime energy demand is higher than the working hours average for most of the buildings. Based on these findings a final set of indicators was compiled. These indicators were found to able to identify characteristics of the building consumption profiles that can be indicative of potential wastage and therefore lead to energy savings.

Several IMT model parameters and load demand shape indicators can be linked to specific opportunities to save energy in the buildings under study. These opportunities for saving energy can be derived from changing buildings' operational management but also occupants' behaviour. For example, reducing wastage from using energy when the building is unoccupied overnight and on weekends, adjustment of heating controls and temperature set points, and even continuous excessive energy use (when compared with buildings of the same type).

This is similar to other studies that have suggested that by analysing building energy consumption data it would be possible to identify potential energy and carbon savings. Although based on monthly energy consumption data and degree-day information, a multi-client study offered in a confidential report (Harris, 1999), presents several types of specific savings that can be identified by building degree-days energy signatures - also regarded as building energy performance lines. The anomalies detected by Peter Harris are based on the visual identification of certain characteristics on the energy performance lines, which may indicate failures or unusual patterns of consumption that can lead to energy savings. The characteristics are defined as deviations from the regression line between energy use and degree-days. According to Harris (1999) there are three common divergences from the straight line: bends, breaks and loops. He states that bends are usually due to a lack of uniform internal temperature conditions. The breaks are caused by changes in the heating strategy or control system, and the loops are verified when there are different energy consumption for similar degree-days values, usually caused by a different inside temperature, different heating hours or different ventilation rate.

Another study of building operation diagnosis presented by Baumman (2006) used 2D contour plots to analyse BEMS data to optimise building energy use. This study concluded that analysis of short time series data can help detect opportunities to save energy to be further investigated on site and discussed with the building manager. The typical opportunities identified by building operation diagnosis concerned the correction of operation times regarding schedules, new or modified control strategies and adjustment of heating and cooling control settings.

A preliminary study of Leicester City Council energy and water metering and monitoring systems is presented in (Ferreira, et al., 2006, 2007). These papers present the context and an overview of Leicester energy agency work, and case studies of identification of energy and water savings in local authority buildings. It was found that savings are achieved by correcting operational management and maintenance procedures. This savings are sometimes described as “low hanging fruits”. In what concerns energy use, the “low hanging fruits” picked up by the metering and monitoring system are typically space heating timer control problems and high energy wastage due to high set point control temperatures, etc.

The CaRB project studied in detail primary meter short time series energy data from Leicester City Council buildings. The data made available to CaRB researchers is the same used in the current work. Initial results from CaRB project (Brown & Wright, 2008; Wright & Brown, 2008) present four common failure modes for building energy consumption. These failure modes are defined as the characteristic manner in which the failure occurs, which can be detected by analysing half-hourly data weekly profiles. The key failure modes are: heating (or cooling) out of season, heating when building unoccupied (on particularly on weekends), high baseloads and excessive continuous consumption.

These studies point out that the analysis of energy and outside temperature data can be useful for identifying a range of potential energy savings opportunities. Peter Harris states that analysis of building energy performance lines by a trained energy practitioner can be used to detect problems in weather related energy consumption. The DYNAMAT software produces graphs and plots that help the municipal energy management team to detect and eliminate energy wastage. The CaRB research project uses the visual inspection of weekly profile plots and expert interpretation to detect four key failure modes in Leicester City Council building electricity and gas consumption. Work is currently being carried out to automate CaRB failure mode detection approach.

Currently, all these approaches are applicable to building energy diagnostics to improve performance, but they do not offer an objective method for analysing data. In fact, all the methods presented are based exclusively on visual analysis of data and subjective interpretation of data and information. Therefore, the effectiveness of the previous data analysis approaches depends, to a great extent, on the expertise of the energy practitioner.

The current work, presents, for the first time, a comprehensive approach that applies measurable and quantifiable parameters for objective data interpretation. This analysis is independent of practitioners experience in building energy data analysis. The application of the approach suggested in the current work is summarised in Figure 52. This diagram links the computed indicators with building energy consumption characteristics that can be indicative of energy wastages, i.e. opportunities to save energy. The potential energy saving opportunities can be found from:

- Fixed, non-weather related energy use;
- Dependency of energy use and temperature during the heating season;
- Base temperature, below which heating systems are turned-on;
- Intensity of energy use;
- Baseload consumption;
- Energy use when building unoccupied on night-time on weekdays;
- Energy use when building unoccupied on night-time on weekends;
- Energy use when building unoccupied on weekends.

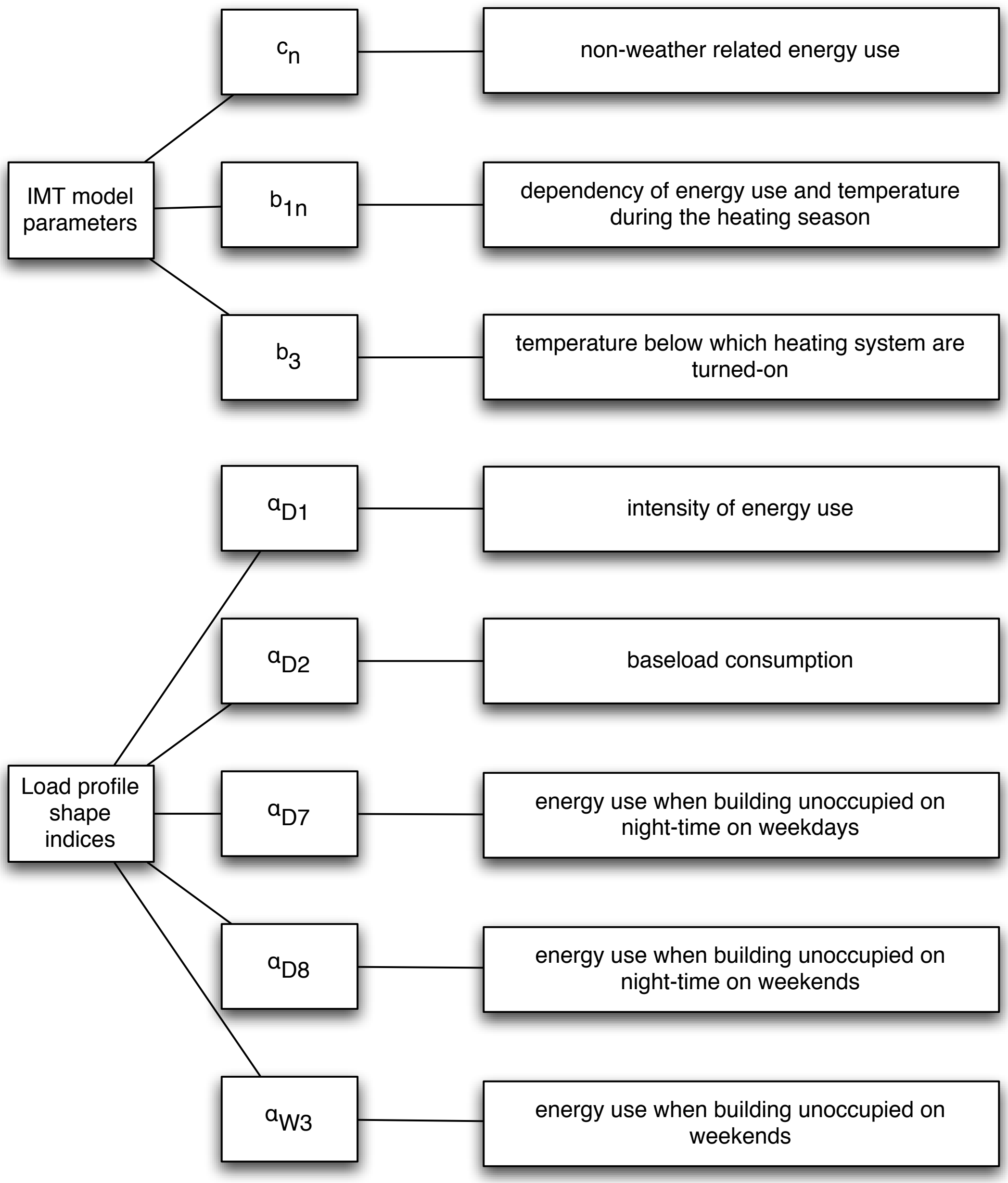


Figure 52. List of relevant indicators and 'failure modes'

These 'failure modes' or potential energy saving opportunities can be used to identify building with uncommon profiles characteristics. However, different buildings types are expected to have distinct consumption profiles, mainly due to different occupancy patterns and energy consumption profiles. For instance, the load factor for SQ21-type buildings (assisted accommodation, and children homes) is expected to be consistently higher than for other buildings. This does not mean that SQ21 buildings perform 'better' or 'worst' than other buildings. The high load factor is caused by the fact that these are usually permanently occupied buildings.

Buildings of the same type and function need to be compared in order to have more meaningful results. The analysis of indicators by building type is presented in the following chapter.

Chapter 8. Analysis of results per building type

The previous chapter presented and analysed the indicators with no breakdown between building types. However, the dataset available offers the classification of building types: office and administrative buildings (CO), museums and libraries (HL1), leisure centres (HL3), schools (SE), community centres (SQ10) and homes and hostels (SQ21), as presented in Table 5.

Buildings in the study have different types, size, construction type, age, occupancy hours, and therefore buildings have different energy needs and different consumption profiles. Nevertheless, it would be expected that buildings of the same type have similar consumption profile characteristics.

A comparative study of indicators for different building types was conducted in order to assess the prospective use of indicators for benchmarking using half-hourly electricity and gas consumption data. Indicators breakdown per building type are presented in this chapter in terms of mean and standard deviation values. Statistical tests were conducted to assess statistically significantly differences between buildings types, both for indicators calculated using electricity and gas consumption data.

8.1. Electricity indicators per building type

The following table presents the indicator mean values for 6 groups of building types calculated for electricity consumption.

Table 20. Electricity load shape indicators mean values per building type

Mean	α_{D1}	α_{D2}	α_{D7}	α_{D8}	α_{W3}
CO	0.50	0.38	0.41	0.90	0.51
HL1	0.46	0.22	0.26	0.43	0.65
HL3	0.76	0.53	0.61	0.67	0.89
SE	0.47	0.40	0.45	1.03	0.47
SQ10	0.51	0.34	0.48	0.82	0.62
SQ21	0.78	0.78	0.87	0.90	0.98

Table 20 shows that indicators mean values vary between building types. However, there are also groups of building types that have similar results. For example, the mean values for α_{D1} indicator, the load factor, is similar for CO, HL1, SE and SQ10 building types (between 0.46 and 0.51) and for HL3 and SQ21 (and between 0.76 and 0.78) building types. Remember that electricity α_{D1} indicator mean value calculated for all the buildings was 0.61.

Another important statistic in the analysis of indicators is the standard deviation values, presented in Table 21. The standard deviation describes the distance of the indicators calculated for each building to the mean value calculated for a type of building. The standard deviation values presented in Table 21 are lower than the standard deviation values on Table 11 calculated for all buildings. The only exception is the standard deviation for indicator α_{D8}, which is 0.21 for all buildings and 0.22 for HL3-type buildings.

Table 21. Electricity load shape indicators standard deviation per building type

Std. dev.	α_{D1}	α_{D2}	α_{D7}	α_{D8}	α_{W3}
CO	0.08	0.12	0.12	0.11	0.14
HL1	0.10	0.14	0.13	0.16	0.16
HL3	0.12	0.23	0.24	0.22	0.13
SE	0.07	0.11	0.12	0.08	0.10
SQ10	0.07	0.12	0.22	0.20	0.21
SQ21	0.09	0.12	0.09	0.09	0.02

The reduced standard deviation suggests that there is in fact consistency for the indicators breakdown per building type. The use of box-plots can provide additional insight on differences between types of buildings. Figure 53 presents the box plot for α_{D1} calculated for electricity consumption. The dots are the real data points. The limits of the box indicate the 75th and 25th percentiles, and the median is the line inside the box. Outside the box in blue there is the mean and the dotted lines are the mean plus and minus one standard deviation. The crosses represent the outliers.

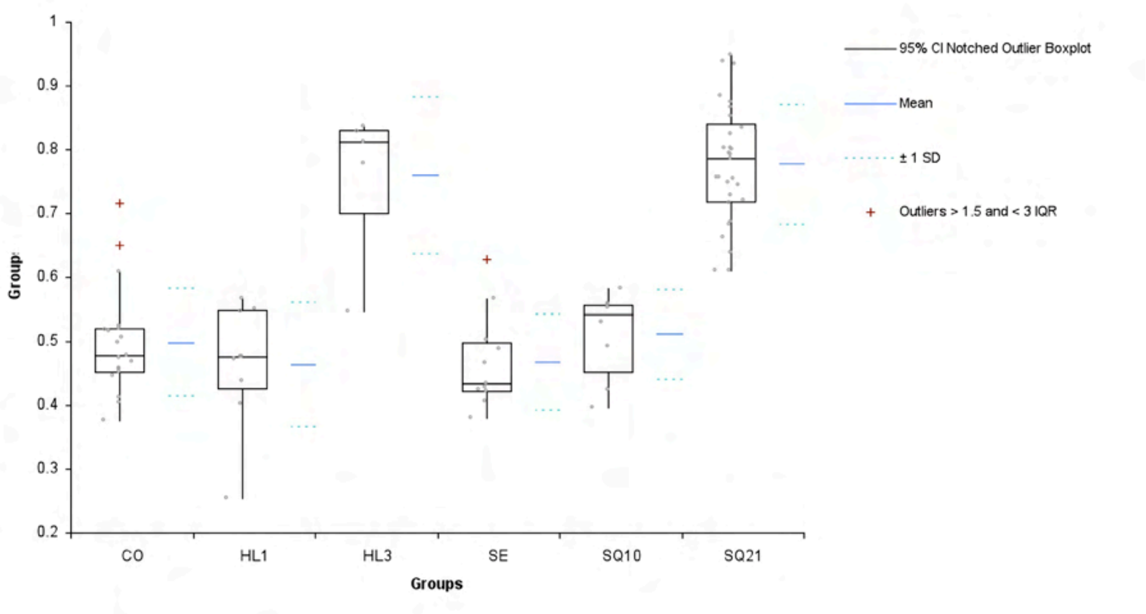


Figure 53. Box plot for electricity α_{D1} indicator per building type

From Figure 53 box plot it is possible to realise that results for HL3 and SQ21 are quite different from results for other building types. Moreover, HL3 and SQ21 have apparently similar means. For the other building types it is possible to identify some similarities, however, there are also some outlier values that affect results.

The assessment of differences between results for the 6 building types was done using suitable statistical methods. The statistics used to test the differences between groups of results for different building types was Tukey HSD (Honest Significant Differences) post-hoc test, (Urdan, 2005). Tukey HSD is typically used to compare the possible differences between pairs of means. The comparisons are preformed between individual means. For example, in our case we have 6 groups/building types (CO, HL1, HL3, SE, SQ10 and SQ21), therefore there are 15 possible paired comparisons.

Tukey HSD test was applied to the 5 (α_{D1}, α_{D2}, α_{D7}, α_{D8} and α_{W3}) sets of indicators calculated for electricity consumption data. The next table presents a summary of results of Tukey HSD test. The means were found to be significantly different for several pairs of building types. The abbreviation 'signif.' stands for statistically significant different means. For example, α_{D1} mean values were found to be significantly different for the pairs: CO-HL3, CO-SQ21, HL1-HL3, HL1-SQ21, HL3-SE, HL3-SQ10, SE-SQ21 and SQ10-SQ21.

Table 22. Tukey HSD summary results for electricity

α_{D1}	CO	HL1	HL3	SE	SQ10	SQ21
CO						
HL1						
HL3	signif.	signif.				
SE			signif.			
SQ10			signif.			
SQ21	signif.	signif.		signif.	signif.	

α_{D2}	CO	HL1	HL3	SE	SQ10	SQ21
CO						
HL1	signif.					
HL3		signif.				
SE		signif.				
SQ10						
SQ21	signif.	signif.	signif.	signif.	signif.	

α_{D7}	CO	HL1	HL3	SE	SQ10	SQ21
CO						
HL1						
HL3	signif.	signif.				
SE		signif.				
SQ10		signif.				
SQ21	signif.	signif.	signif.	signif.	signif.	

α_{D8}	CO	HL1	HL3	SE	SQ10	SQ21
CO						
HL1	signif.					
HL3	signif.	signif.				
SE		signif.	signif.			
SQ10		signif.		signif.		
SQ21		signif.	signif.			

α_{W3}	CO	HL1	HL3	SE	SQ10	SQ21
CO						
HL1						
HL3	signif.	signif.				
SE		signif.	signif.			
SQ10			signif.			
SQ21	signif.	signif.		signif.	signif.	

It is possible to say that in fact building types are characterised by different indicators values. However, there are groups of building types that do not have statistically different means. For example, the load factor (α_{D1}) mean values are not statistically different for offices, libraries, museums, schools and community buildings – i.e. CO, HL1, SE and SQ10 building types. Similarly, the load factor (α_{D1}) mean values are not statistically different for sports halls, homes and hostels – i.e. HL3 and SQ21 building types. Nevertheless CO, HL1, SE and SQ10 mean load factors are statistically different from the mean load factor of HL3 and SQ21.

In conclusion, groups of buildings of the same type have statistically different results for the different indicators computed for electricity consumption data, except for the pairs identified by Tukey HSD post-hoc test, presented in the table above.

8.2. Gas indicators per building type

The indicator results for gas consumption data by building type are presented in the following tables. Table 23 shows that the indicators mean values vary between building types. Similarly to what was found for electricity use, there are also groups of building types with apparently similar mean values. For example, the mean values for α_{D1} indicator, the load factor, is similar for CO, HL1, SE and SQ10 building types (between 0.43 and 0.52) and for HL3 and SQ21 (and between 0.69 and 0.76) building types. Remember that gas α_{D1} indicator mean value calculated for gas consumption of all buildings was 0.60.

Table 23. Gas indicators mean values per building type

Mean	α_{D1}	α_{D2}	α_{D7}	α_{D8}	α_{W3}	c_n	b_{1n}	b_3
CO	0.52	0.39	0.60	0.80	0.78	0.12	-0.36	17.96
HL1	0.49	0.27	0.68	0.71	0.78	0.09	-0.43	16.91
HL3	0.69	0.53	0.64	0.69	0.97	0.45	-0.30	18.00
SE	0.43	0.21	0.46	0.71	0.50	0.20	-0.34	18.36
SQ10	0.46	0.30	0.55	0.68	0.74	0.11	-0.31	18.85
SQ21	0.76	0.63	0.85	0.86	1.00	0.33	-0.18	18.62

The standard deviation values presented Table 24 are high when compared to the mean values. Standard deviation values for gas indicators were found to be higher than the ones determined for electricity indicators. This was probably due to the seasonal variation of gas use, and the fact that for some buildings gas is turned off completely in summer, while in others there is gas usage during these months – non-weather related gas.

Table 24. Gas indicators standard deviation per building type

Std. dev.	α_{D1}	α_{D2}	α_{D7}	α_{D8}	α_{W3}	c_n	b_{1n}	b_3
CO	0.24	0.35	0.32	0.30	0.30	0.10	0.11	0.90
HL1	0.20	0.32	0.47	0.45	0.24	0.13	0.13	0.74
HL3	0.26	0.30	0.26	0.18	0.04	0.12	0.35	5.35
SE	0.19	0.28	0.30	0.41	0.30	0.14	0.10	1.41
SQ10	0.20	0.37	0.44	0.41	0.34	0.08	0.09	1.69
SQ21	0.13	0.27	0.14	0.14	0.02	0.10	0.04	1.02

This characteristic of gas indicators can be presented more clearly using box plots of indicators results for the different building types. Figure 54 presents the box plot for gas α_{D1} indicator with a breakdown by building type. From this plot is possible to see the wide boxes that represent the distribution of data points from the 25th percentile to the 75th percentile. It is also possible to identify the high standard deviation values compared to the mean for gas consumption of all building types.

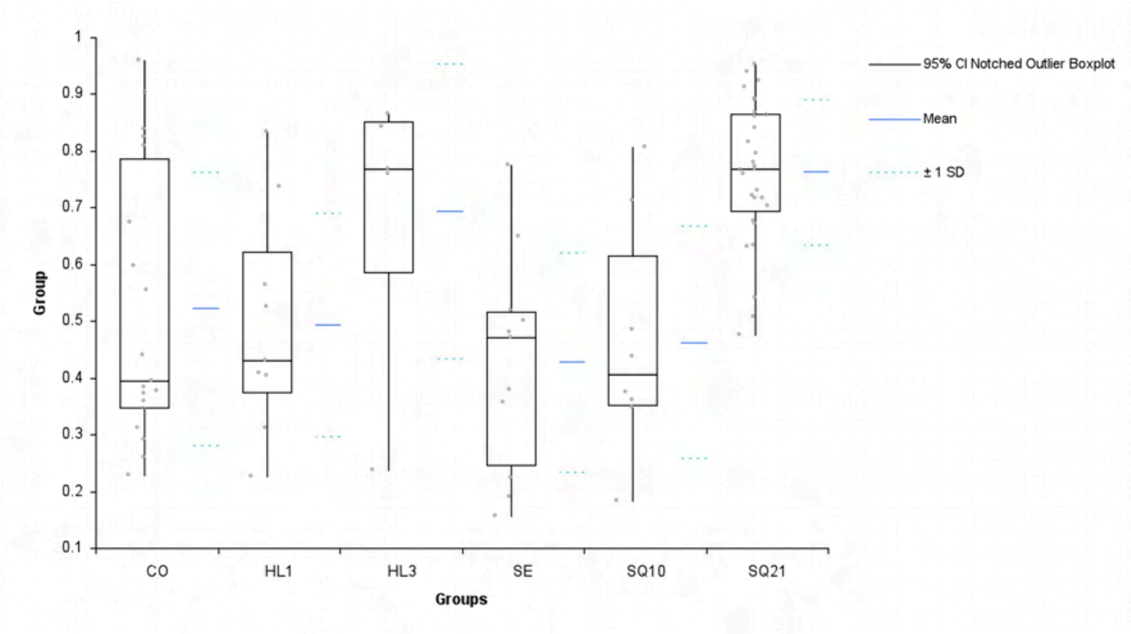


Figure 54. Box plot for gas α_{D1} indicator per building type

The following box plots present the results of c_n, b_{1n} and b_3 indicators per building type. Generally, the standard deviation values found for IMT model parameters are not as high as values found for load demand shape indicators. Although IMT model parameters have significant dispersion for some indicators and building types.

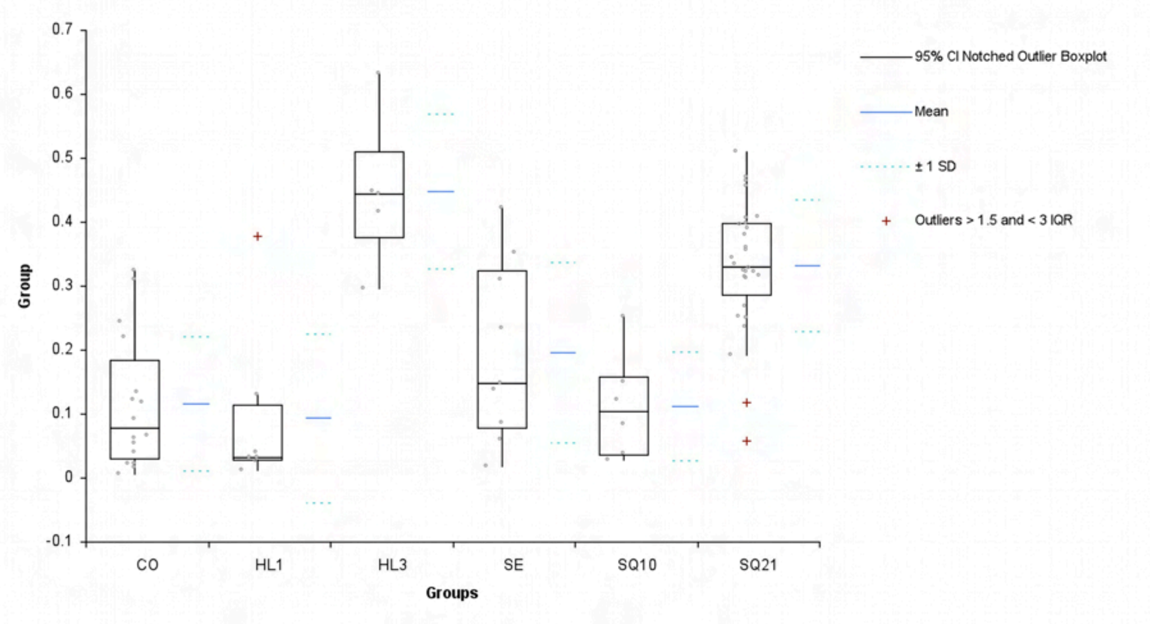


Figure 55. Gas c_n indicator mean and standard deviation values per building type

Concerning the non-weather related energy use, presented in Figure 55, the mean values of CO, HL1, SE and SQ10 building types are found to be close. They were similar to results found for HL3 and SQ21 building types.

This leads to an important finding concerning energy use for other uses that are not space heating (e.g. hot water and cooking). From this plot it can be said that the mean non-weather related energy use is usually less than 20% for office buildings (CO), library and museums (HL1), schools (SE) and community centres (SQ10) in Leicester. However, it is also possible to say that there are a few schools (SE) that use more gas for hot water and cooking, than the average assisted home or hostel, which are typically permanently occupied buildings. In fact, the non-weather related gas use varies greatly between schools, and is more dispersed results than other building types presented above. This is probably caused by the fact that some schools in Leicester are in charge of producing meals that are distributed to other schools, which do not have kitchens.

The next plot, in Figure 56 presents the results for b_{1n}, the slope of regression line of below the change-point temperature, and normalised by total energy use. This indicator represents the gas needed to heat the building for each degree-Celsius decrease of outside temperature. Results of b_{1n} for leisure centres (HL3) are dispersed probably because these include sports halls with and without swimming pools, which affects notably the heating demand profile. Care homes and hostels (SQ21) have the less dispersed results for b_{1n}, with very little variations from building to building. These are permanently occupied and therefore permanently heated buildings. The heating demand profile of these buildings is more uniform, usually constant and regulated by automatic controls and fixed temperature set-points.

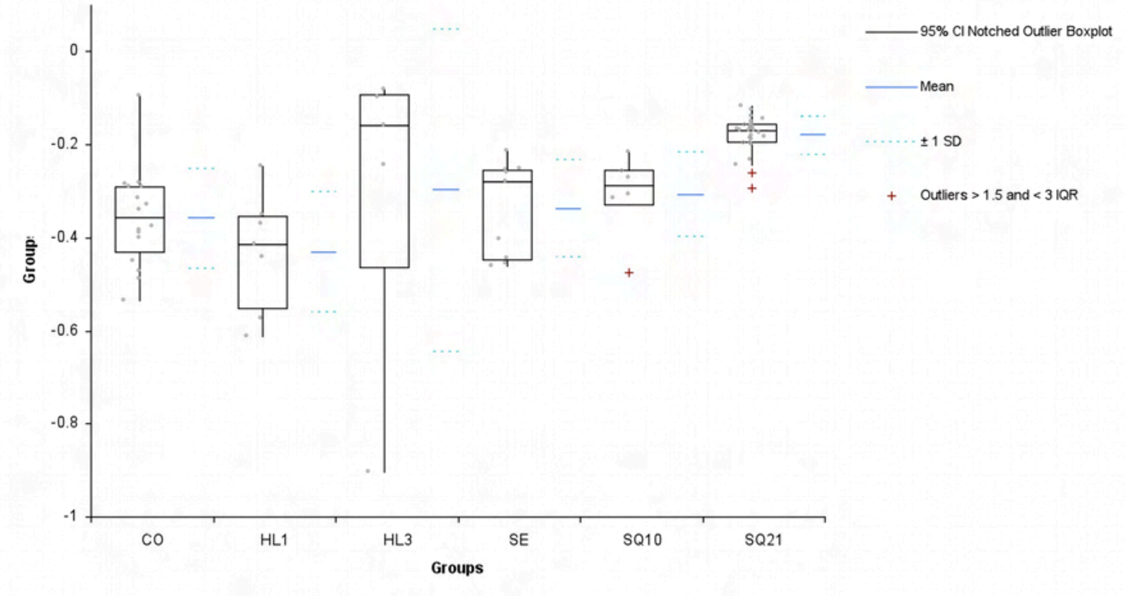


Figure 56. Gas b_{1n} indicator mean and standard deviation values per building type

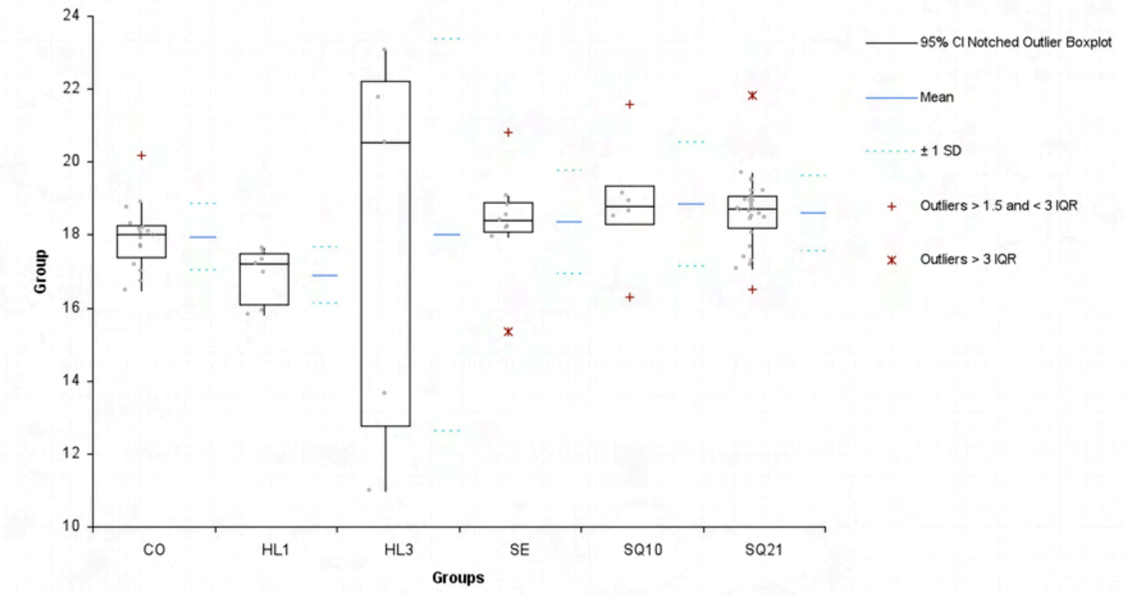


Figure 57. Gas b_3 indicator mean and standard deviation values per building type

The results for the change-point temperature are presented in Figure 57. The b_3 indicator, expressed in degree-Celsius units, represents the temperature below which space-heating system is turned on. Mean values are similar for all building types, except for leisure centres (HL3). Again, this is probably caused by the existence or not of swimming pools.

To increase the objectivity in the analysis of gas consumption indicators, and to statistically assess the similarities between results for different building types Tukey HSD tests were applied. The following table presents the summary results of Tukey HSD tests.

Table 25. Tukey HSD summary results for gas

α_{D1}	CO	HL1	HL3	SE	SQ10	SQ21
CO						
HL1						
HL3						
SE						
SQ10						
SQ21	signif.	signif.		signif.	signif.	

α_{D2}	CO	HL1	HL3	SE	SQ10	SQ21
CO						
HL1						
HL3						
SE						
SQ10						
SQ21		signif.		signif.		

α_{D7}	CO	HL1	HL3	SE	SQ10	SQ21
CO						
HL1						
HL3						
SE						
SQ10						
SQ21				signif.		

α_{D8}	CO	HL1	HL3	SE	SQ10	SQ21
CO						
HL1						
HL3						
SE						
SQ10						
SQ21						

α_{W3}	CO	HL1	HL3	SE	SQ10	SQ21
CO						
HL1						
HL3						
SE	signif.		signif.			
SQ10						
SQ21	signif.			signif.	signif.	

c_n	CO	HL1	HL3	SE	SQ10	SQ21
CO						
HL1						
HL3	signif.	signif.				
SE			signif.			
SQ10			signif.	signif.		
SQ21	signif.	signif.		signif.	signif.	

b_{1n}	CO	HL1	HL3	SE	SQ10	SQ21
CO						
HL1						
HL3						
SE						
SQ10						
SQ21	signif.	signif.		signif.		

b_3	CO	HL1	HL3	SE	SQ10	SQ21
CO						
HL1						
HL3						
SE						
SQ10						
SQ21						

From the summary of results presented above it is possible to say that building types have different indicator values calculated for gas consumption. However, there are fewer differences between building types than the differences found for electricity. Groups of building types that do not have statistically different means is greater for gas than for electricity. For example, the load factor (α_{D1}) for electricity mean values are not statistically significantly different for offices (CO), libraries and museums (HL1), schools (SE) and community buildings (SQ10), but also for leisure centres (HL3). The load factor (α_{D1}) for gas mean value is only statistically significantly different for care homes and hostels (SQ21) building type.

For the night impact on weekends (α_{D8}) and change-point temperature (b_3) it was found no statistically significant differences between building types. This suggests that mean values of these two indicators can be considered to be similar across all buildings.

In conclusion, groups of buildings of the same type have statistically different results for the indicators computed for gas consumption data, except for the pairs identified by Tukey HSD post-hoc test, presented in the table above. The number of pairs for which gas indicators are statistically different is fewer than the number of pairs for which electricity indicators were found to be statistically different. This is due to the fact that gas indicators have higher dispersion and higher standard deviation values, which makes it difficult to clearly differentiate indicator results between similar groups of buildings.

8.3. Chapter summary

In this chapter it was found that building types have statistically different indicators. However, this it not true for all indicators. There are some groups of building types for which the means are not statistically different, based on the results of Tukey HSD post-hoc tests.

Load demand shape indicators computed for electricity consumption data have generally lower standard deviation values, than the same indicators calculated for gas consumption. From a breakdown of IMT model parameters it was possible to conclude that the average non-weather related (c_n) gas consumption varies significantly according to building type. However, this is not so significant for the space heating demand profile (b_{1n}), for which some building types have statistically different means. It was also found that change-point temperatures (b_3) could be considered similar for all the building types.

Some building types have statistically different results and therefore it is possible to set typical values for the load demand shape indicators and IMT model parameters for those groups of buildings. Typical values are the expected results for individual indicators for each building type. These typical values are represented by the mean values, and standard deviation from the mean represents the possible variability from the expected or typical results. The mean and standard deviation values can then be used for setting 'standards' against which electricity and gas consumption indicators can be compared in a benchmarking exercise.

As presented earlier, energy managers and practitioners apply benchmarks to assess building performance. Usually these benchmarks are NPI based on annual energy consumption, as calculated in chapter 5 for the buildings under study.

This research attempts to define and test empirical benchmarks for building energy management based on daily and half-hourly electricity and gas consumption data. The following chapter presents the application of these empirical benchmarks to available data using those load demand shape indicators and IMT model parameters found to be related to potential opportunities to save energy.

Chapter 9. Benchmarking with half-hourly and daily electricity and gas consumption

However normally carried out using total annual energy consumption data, benchmarking is a very common approach used in building energy performance assessment. As presented in the literature review, in chapter 2, benchmarking is a common building energy diagnostics tool, usually applied to annual data. From the survey results presented in chapter 4, it was found that empirical benchmarks are much appreciated by municipal energy managers. Survey findings refer to the use of benchmarks by comparing their own buildings stock, but also applying national published standards or typical NPI values. Conventional empirical benchmarks illustrate the overall performance, i.e. a figure of energy use in kWh/m^2 per year in comparison with a typical consumption calculated for the same building type also in kWh/m^2 per year. However, a more interesting way of conducting benchmarking would be to assess how the building energy performance is achieved.

This thesis is based on the development and application of empirical models of electricity and gas to assess the building performance and infer potential energy saving opportunities. These models are provided with readily available primary meter electricity and gas data in daily and half-hourly periods, and produced a set of outputs in the form of indicators that characterise the load demand curve and the relationship between energy consumption and outside temperature. Therefore, it should be possible to develop empirical benchmarks based on these model output indicators. Empirical benchmarks can be understood as the comparison of actual building energy consumption against a wider population of buildings of similar type, function and occupancy hours. The load demand indicators calculated are comparable between buildings of the same type, because they are only dependent on the shape of the load demand curve, and not the building size or total demand. However, it was necessary to normalise the non-weather gas use (parameter c) and the slope of the regression line (b_1) for building size. This normalisation procedure was explained in chapter 7. Normalisation of indicators for climate was not required since the buildings were located in the same city.

This chapter presents a benchmarking exercise for Leicester City Council buildings. No evidence was found that similar exercise has been conducted elsewhere. This benchmarking study was limited to available data and therefore results are not generalised to other non-domestic buildings in the UK or elsewhere. However, if additional data was made available it should be possible, in theory, to develop national benchmarks based on half-hourly electricity and gas data.

9.1. Standardisation of results

The electricity and gas short time series indicators described previously were used to characterise performance, in terms of demand profiles and thermal behaviour. These indicators can support a new benchmarking framework linked to the causes of performance, and not to the absolute measure of performance, as NPI.

Conventional benchmarks figures are usually calculated using percentile ranks. The 25th, median and 75th percentiles are usually considered to be thresholds of good, normal and bad energy performance, (Jones, et al., 1991). However, according to Jones the calculation of energy benchmarks requires large samples with more than 100 buildings. In the current study the size of samples vary from 29 buildings for SQ21-type buildings, to 5 buildings for HL3-type buildings. The percentile rank method used to calculate benchmarks did not produce satisfactory results. The reason was the fact that percentiles were extremely sensitive to the small number of buildings in each sample. For example, if the 75th percentile is set as normal threshold value to a group with 5 buildings, (i.e the 4th higher element) there will be at least 2 elements (out of 5) outside the typical consumption band.

Standard scores, or z-scores, were used instead of percentiles. This standardisation method is based on the mean and standard deviation values, and was used to identify the distance from the mean value of each calculated indicator (Urdan, 2005).

The z-score - z_i associated with each indicator value x_i is given by Equation 24; where x_i is subtracted by the mean value and divided by the standard deviation of all observations in the group (buildings of the same type).

$$z_i = \frac{x_i - \bar{x}}{\sigma}$$

Equation 24. Standard score calculation

This standardisation process allows easy comparison of indicator results for the different buildings of the same type. A standard score of 1.00 is a result of an element that is above the mean by exactly one standard deviation. If the values follow a normal distribution, a standard score of 1.00 is equivalent to 84.13% of the values (percentile 84^{th}). In the current study one considered that standard scores above 1.00 were considered outside the expected in terms of a 'normal' energy consumption profile, and therefore were indicative of potential energy wastage. One standard deviation was found to be a sensitive point of reference for setting the benchmark. Further research will show if this is the case.

For example, taking 16 New Walk building, the indicator α_{D1} calculated for electricity consumption is 0.52, as presented in Table 12. From Table 20 and Table 21 it is possible to realise that the mean value for CO-type buildings is 0.50 and the standard deviation 0.08. Therefore, the standardised score for α_{D1} indicator calculated for 16 New Walk electricity consumption is 0.25, as presented in Table 26. This value is within the acceptable standardised score range (below 1.00).

Conversely, Attenborough House with an electricity load factor (α_{D1}) of 0.72, results in a standard score of 2.60. This score is above 1.00 and therefore outside what is considered to be a 'normal' result. Therefore, it is possible to say that Attenborough house load factor (α_{D1}) for electricity consumption is significantly above the mean load factor for electricity use in office buildings in Leicester. Consequently, this may be indicative that Attenborough house suffers from continuously high energy consumption (when compared with buildings of the same).

All the results of standardised scores for all the buildings are presented in the following sections for electricity and gas consumption. The red shading in the tables indicates standardised values that are outside what is considered to be the range of common consumption profile, i.e. above one standard deviation from the mean value of the building type.

9.2. Electricity consumption benchmarking per building type

This section presents the standard scores for electricity indicators for the 6 building types.

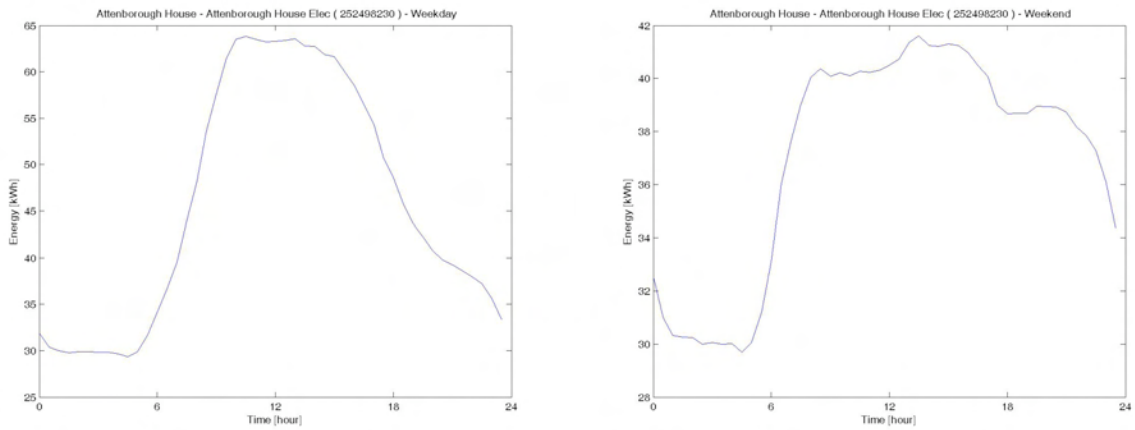
Table 26 presents the standard scores for Leicester City Council office and administrative buildings electricity consumption (CO-type buildings). Scores above 1.00 are presented in red shading.

Table 26. Standard scores for electricity indicators and CO-type buildings

Standard Score	α_{D1}	α_{D2}	α_{D7}	α_{D8}	α_{W3}
308 Melton Rd Elec	0.08	0.24	0.35	-1.73	1.20
16 New Walk Elec	0.25	-0.85	-0.95	0.71	-1.15
47 New Walk Elec	-1.04	-0.96	-1.08	0.97	-1.44
Attenborough House Elec	2.60	2.24	2.30	-0.32	2.46
Home Farm AHO Main Elec	-1.13	-1.38	-1.49	-2.16	-0.93
Charnwood AHO Main Elec	-1.48	-0.40	-0.56	0.21	-0.66
Energy Office Elec	0.00	0.19	0.35	-0.15	0.11
Home Improvement Agy Elec	-0.63	-0.13	-0.26	1.22	-0.53
Humberstone AHO Main Elec	-0.50	-0.63	-0.66	-1.07	-0.05
Marlborough House Elec kWh	-0.24	-1.18	-1.29	0.55	-1.49
New Parks AHO Elec	0.29	0.65	0.67	0.92	0.36
New Walk B Block Elec kWh	1.80	1.83	1.66	0.37	1.29
Phoenix House Elec kWh	0.22	-1.00	-0.72	-0.81	-0.58
Rowsley St AHO Elec	-0.51	0.67	0.47	0.71	0.22
Saffron AHO Elec	-0.36	-0.71	-0.44	0.06	-0.32
Sth Braunstone AHO Elec	-0.30	-0.32	0.10	0.91	-0.15
St Marks AHO Main Elec	-0.56	0.03	-0.16	-1.41	0.42
Tudor Centre Elec	0.20	0.63	0.66	0.89	0.47
Town Hall Elec kWh	1.30	1.07	1.05	0.14	0.78

The building with the highest scores is Attenborough House office building, in particular α_{D1}, α_{D2}, α_{D7} and α_{W3} indicators. New Walk B Block and the Town Hall have also probable excessive energy use (α_{D1}), high baseload (α_{D2}) and high night-time consumption on weekdays (α_{D7}). Other office buildings were found to have high night-time electricity consumption on weekends (α_{D8}) and high weekend electricity consumption (α_{W3}), when compared with buildings of the same type.

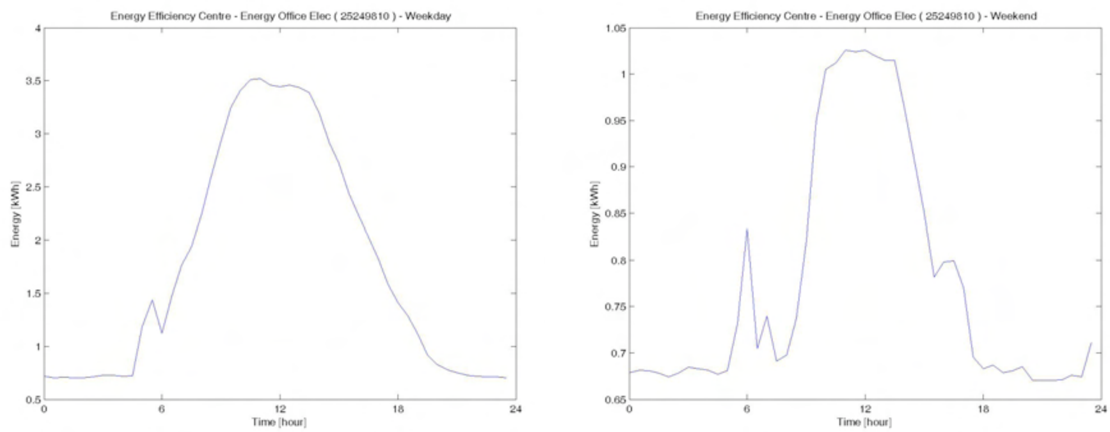
In the case of Attenborough House, electricity consumption indicators are above what is expected, probably because this is not a normal office building. Attenborough House comprises Inland Revenue offices and a snooker bar in the ground floor, which is open until midnight. The electricity load demand profile (weekdays) for Attenborough House is presented in Figure 58. From this annual average profile it is possible to see that it is in fact a building with high baseload consumption, about 30 kWh, and the peak demand is more than twice the baseload. From the plot it is also possible to see that the building is occupied from 6h00 to around 24h00.



Weekday Weekend

Figure 58. Attenborough House electricity demand profile – weekdays and weekend

Attenborough House intensive electricity use, high baseload, and night-time consumption on weekdays is visually more evident when compared with a 'normal' profile building. The Energy Efficiency Office is a 'normal' profile building, with indicators close to the mean values of CO-type buildings. The differences between the profiles is clear, particularly in what concerns the occupancy hours, proportional differences between baseload and peak demand, night-time and daytime consumption, weekday and weekend consumption.



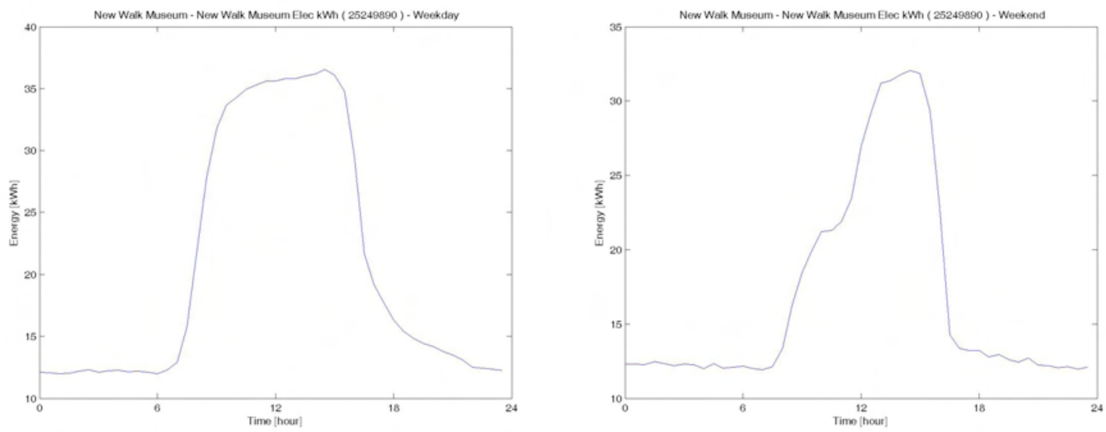
Weekday Weekend

Figure 59. Energy Office electricity demand profile - weekdays and weekend

Table 27 presents the standard scores for Leicester City Council museums and libraries electricity consumption (HL1-type buildings). The building with the higher scores was found to be the New Walk Museum. This building was found to have slightly high load factor (α_{D1}), high baseload (α_{D2}), high night-time consumption on weekdays and weekends (α_{D7} and α_{D8}), and electricity consumption on weekends (α_{W3}).

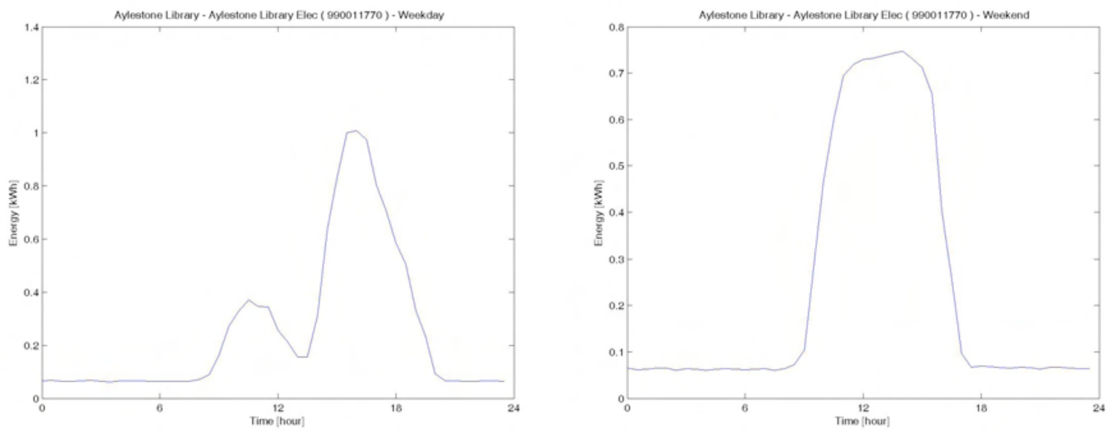
Table 27. Standard scores for electricity indicators and HL1-type buildings

Standard Score	α_{D1}	α_{D2}	α_{D7}	α_{D8}	α_{W3}
New Walk Museum Elec kWh	1.07	2.55	2.45	1.88	1.33
The City Gallery Elec	-0.66	-0.48	-0.70	-0.88	0.10
Aylestone Library Elec	-2.19	0.15	-0.07	-1.01	1.90
Belgrave Library Elec	0.13	-0.63	-0.49	-0.38	-0.50
Central Library Elec kWh	0.86	-0.38	-0.01	-0.02	-0.51
Reference Library Elec	0.88	-0.22	0.36	0.54	-0.43
Evington Library Elec	-0.28	-0.61	-0.75	-1.06	0.07
Southfields Library Elec	0.07	0.13	-0.06	1.04	-1.05
Westcotes Library Elec	0.12	-0.51	-0.74	-0.11	-0.91



Weekdays Weekend

Figure 60. New Walk Museum electricity demand profile – weekdays and weekend



Weekdays Weekend

Figure 61. Aylestone Library electricity demand profile – weekdays and weekends

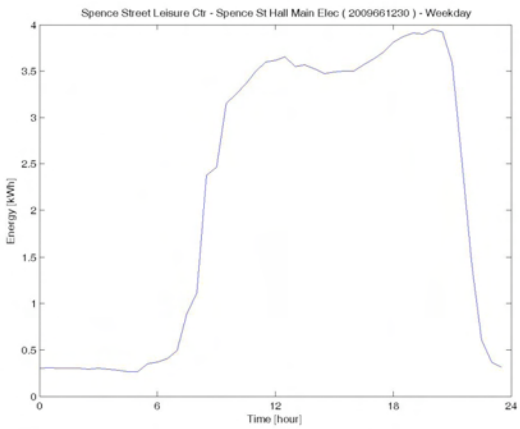
Note that the New Walk Museum is the only museum in the group. The other buildings are libraries and there is also an art gallery. Figure 60 presents the average electricity demand profile of New Walk Museum and Figure 61 the same profile but for Aylestone library. New Walk Museum is open for longer hours than libraries, and uses electricity for air conditioning including humidity control. From Aylestone library profile it is possible to see that it was open mainly on the afternoon of weekdays, and Saturdays all day. Once again, load demand shape indicators and standardised scores modelled electricity profile differences for these buildings detected uncommon profile characteristics quite effectively.

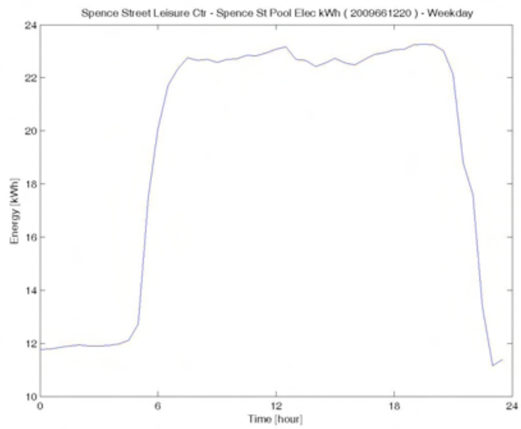
For Leisure centres, HL3-type buildings, presented in Table 28, no indicator was highlighted. HL3-type buildings include leisure centres with and without swimming pools.

Table 28. Standard scores for electricity indicators and HL3-type buildings

Standard Score	α_{D1}	α_{D2}	α_{D7}	α_{D8}	α_{W3}
Aylestone Les Main Elec kWh	0.42	0.40	0.52	0.42	0.70
New Parks Les Main Elec kWh	0.14	0.59	0.48	0.43	0.43
Spence St Hall Main Elec	-1.76	-1.77	-1.77	-1.77	-1.77
Coss Pool Elec kWh	0.63	0.56	0.57	0.66	0.33
Spence St Pool Elec kWh	0.56	0.22	0.20	0.26	0.31

For example, Spence Street Hall is a sports hall without swimming pool. However, an adjacent site, Spence Street Pool includes a swimming pool. The electricity load demand profiles for these building are presented in Figure 62.





Spence Street Hall Spence Street Pool

Figure 62. Spence Street Hall and Pool electricity demand profile – weekdays

The profiles are different particularly in relation to baseloads and peak loads. As expected, the swimming pool has a more intensive energy use than the sports hall. However, the occupancy hours are similar for both buildings. Nevertheless, the standard score method was not able to identify any building in this group. This was mainly because this group of

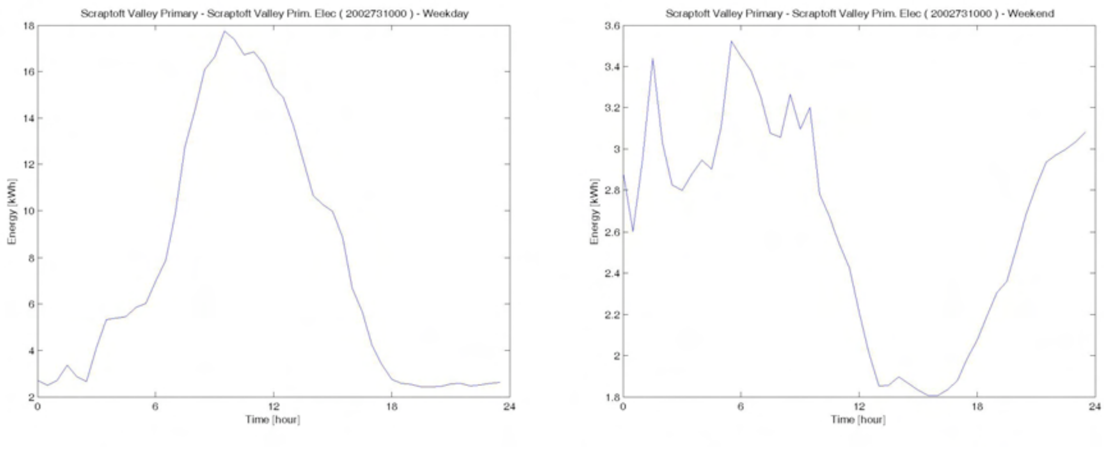
HL3-type buildings is just a sample of 5 very different buildings, including dry and wet sports halls and this resulted in a sample with high standard deviation. This is a major limitation of standard scores use, because when standard deviation is high, standardisation range becomes very wide. A more detailed breakdown of building types could have been introduced. Swimming pools should have been analysed separately from sports halls. However, due to the limited number of Leisure centre type building (only 5 buildings) it was decided to include all in the same building category.

Table 29 presents the standardised scores for school buildings (SE-type buildings) From this table it is possible to identify that Ash Field School and Millgate Centre have the highest scores for most of the indicators. Intensive energy use of electricity and high baseload is a common feature to both schools. Ash Field School has high night-time impact on weekdays and weekends, and Millgate Centre has slightly high electricity use on weekends. It is interesting to note that both these schools are special schools. Special schools have specific electricity uses that is not present in other schools, for example wheelchair charging, motors for opening and closing doors, etc. These electricity uses are probably the cause of identified differences in electricity consumption profiles.

Table 29. Standard scores for electricity indicators and SE-type buildings

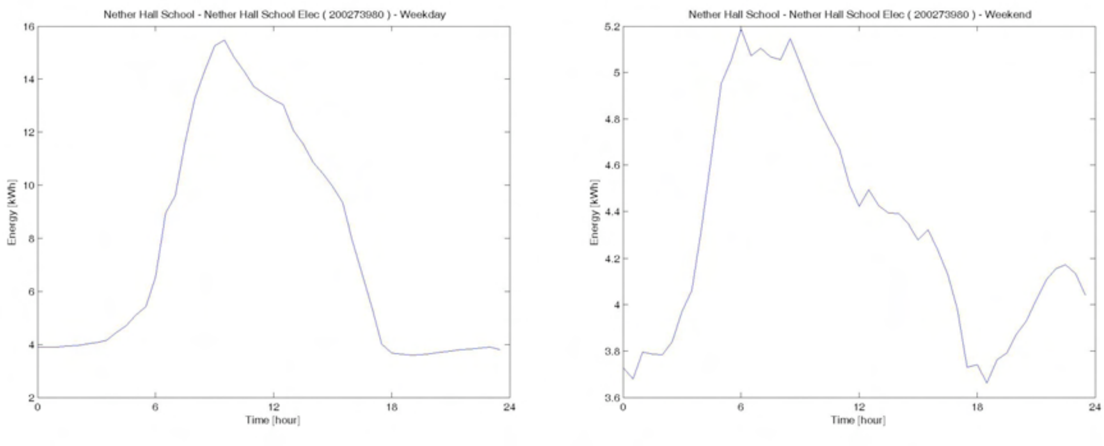
Standard Score	α_{D1}	α_{D2}	α_{D7}	α_{D8}	α_{W3}
Lansdowne Pre School Elec	-0.58	-0.75	-1.06	-0.57	-0.86
Catherine Jnr School Elec	-0.46	0.55	0.08	-0.03	0.63
Heatherbrook Sch Elec	-0.84	-0.52	-0.36	1.00	0.00
Scraptoft Valley Prim. Elec	-0.53	-0.72	0.27	1.32	-0.41
Thurnby Lodge Primary Elec	-1.19	-1.16	-1.01	0.50	-1.30
Whitehall Sch Main Elec	-0.61	-0.60	-0.84	0.50	-1.12
Judgemeadow CC Elec kWh	-0.01	-1.06	-1.02	-1.47	-0.85
New College Main Elec kWh	0.45	0.51	0.24	-1.01	0.85
Ash Field School Elec	2.15	1.78	2.17	1.38	0.21
Millgate Centre Elec kWh	1.33	1.24	0.71	-0.75	1.10
Nether Hall School Elec	0.26	0.74	0.82	-0.87	1.75

Other schools have also been highlighted for uncommon consumption profiles. Heatherbrook School and Scraptoft Valley Primary School, in Figure 63 were identified for high electricity use on weekends over night. Netherhall School was identified for high electricity weekend consumption. The profile for this school is presented in Figure 64.



Weekdays Weekend

Figure 63. Scraptoft Primary School electricity demand profiles – weekdays and weekend



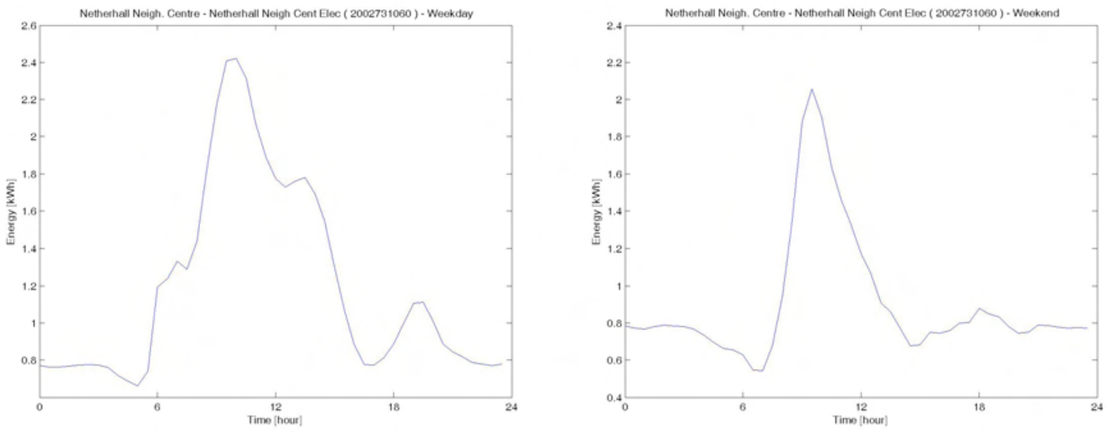
Weekdays Weekend

Figure 64. Netherhall School electricity demand profiles – weekdays and weekend

Table 30 presents the standard scores for electricity consumption of community centres in Leicester.

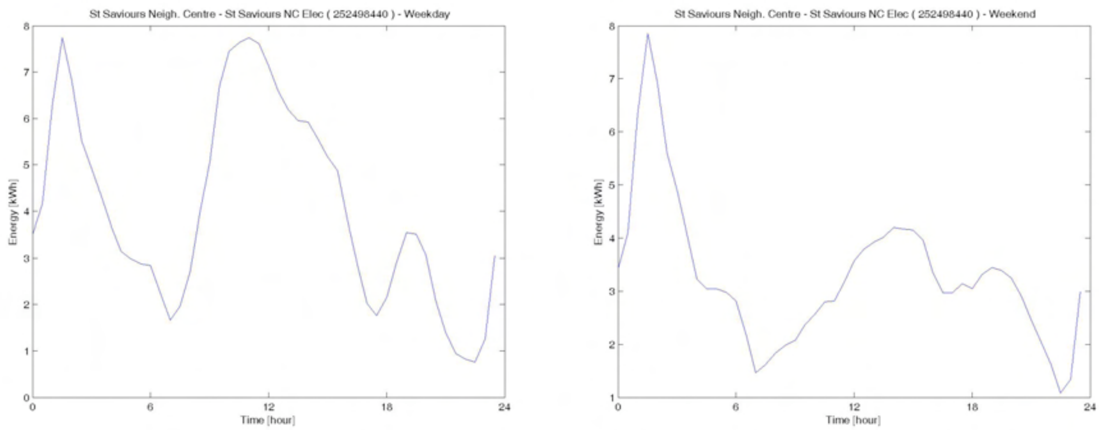
Table 30. Standard scores for electricity indicators and SQ10-type buildings

Standard Score	α_{D1}	α_{D2}	α_{D7}	α_{D8}	α_{W3}
Coss Fam Centre Elec	-1.69	-1.30	-1.17	0.79	-1.83
Belgrave Neigh. Cent Elec	1.05	-0.05	0.08	-1.11	0.89
Braunstone Oak NC Elec	0.67	0.14	-0.55	0.18	-0.64
Coleman Neigh Cent Elec	0.65	0.58	-0.25	-0.48	0.07
Lansdowne Neigh Cent Elec	-1.28	0.00	-0.51	-1.29	0.08
Netherhall Neigh Cent Elec	-0.28	1.81	0.68	0.05	0.92
St Saviours NC Elec	0.27	-1.29	2.10	1.80	1.10
Welford House Elec kWh	0.61	0.11	-0.38	0.05	-0.60



Weekdays Weekend

Figure 65. Netherhall NC electricity demand profiles – weekdays and weekend



Weekdays Weekend

Figure 66. St. Saviours NC electricity demand profiles – weekdays and weekend

From this table Belgrave, Netherhall and St. Saviours Neighbourhood Centres (NC) stand out from the group. Belgrave NC was identified for having a slightly high (score 5% above the threshold value 1.00) load factor. Netherhall NC was identified has having high baseload, as it could be visible in Figure 65. St. Saviours NC was identified has having high night-time electricity use on weekdays and on weekends, and also high electricity use on weekends. Figure 66 presents the profiles for St. Saviours weekdays and weekends. According to Leicester energy management team, these NC have extended occupancy hours, however St. Saviours overnight electricity use should be investigated.

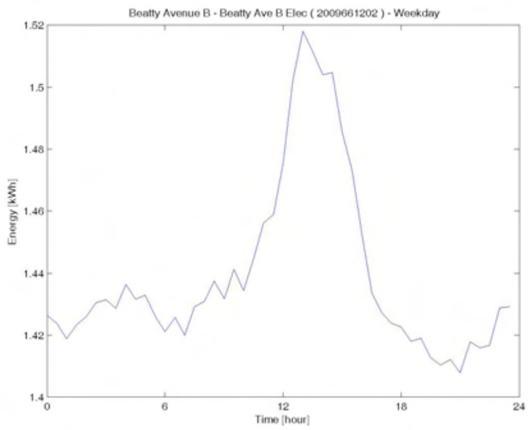
Table 31. Standard scores for electricity indicators and SQ21-type buildings

Standard Score	α_{D1}	α_{D2}	α_{D7}	α_{D8}	α_{W3}
Abbey House EPH Elec	-0.52	-0.24	-0.28	-0.26	-0.48
Arbor House EPH Elec	-0.35	-0.37	-0.57	-0.64	-0.01
Barnes Heath House Elec	0.95	0.33	1.63	1.46	1.47
Barnett Janner WAA Elec	0.19	0.58	-0.13	-0.30	0.77
Beatty Ave B Elec	1.84	1.71	1.23	1.11	0.18
Beaumanor Hostel Elec	-1.51	-2.50	-2.68	-2.67	-0.65
Bowder House WAA Elec	-0.23	1.10	0.68	0.82	-0.49
Bridges House WAA Elec	-0.67	-0.73	-0.93	-1.18	0.80
Butterwick Elec	1.16	0.55	1.64	1.41	0.95
Cromwell House WAA Elec	1.73	1.80	1.16	1.03	1.81
Dudley House WAA Elec	0.10	-0.19	-0.60	-0.74	0.40
Elizabeth House EPH Elec	-0.25	0.24	-0.09	-0.20	0.39
Fred.Thorpe WAA Elec	0.61	-0.50	0.01	-0.14	0.47
Gumbrill House WAA Elec	1.69	1.33	0.86	0.71	0.50
Helena Roberts WAA Elec	-1.81	0.23	-0.60	-0.05	-2.06
Herrick Lodge EPH Elec	-0.62	-0.55	-1.21	-0.77	-2.10
Jackson House WAA Elec	0.50	0.09	-0.46	-0.59	0.25
Lough Rd Hostel Elec	0.27	-0.16	0.68	0.67	-0.43
31 Lower Hastings St Elec	0.15	-1.56	-0.47	-0.84	1.47
33 Lower Hastings St Elec	-0.23	-0.53	-0.27	-0.30	-0.01
Netherhall Childrens Elec	-1.81	-0.71	-0.45	-0.53	0.47
Norfolk House WAA Elec	0.80	1.36	0.99	0.82	0.77
Nuffield House EPH Elec	-1.02	-1.37	-1.08	-0.98	-0.57
Pollard House WAA Elec	-0.31	-0.29	-1.24	-1.33	0.10
Preston Lodge EPH Elec	-0.98	-1.13	-0.78	-0.53	-0.37
Rupert Hse WAA Elec	1.05	1.32	1.07	1.21	-0.46
Tatlow Rd Comm Home Elec	0.25	0.91	0.89	1.31	-2.22
Thurncourt EPH Elec	-1.24	-0.34	0.60	1.14	-1.08
38 Upper Titchbourne Elec	0.26	-0.20	0.43	0.35	0.14

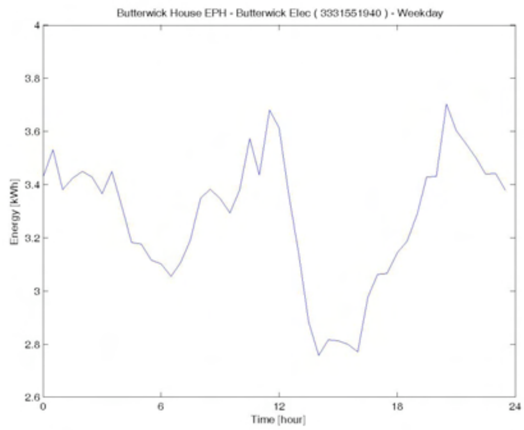
Table 31 presents the standard score results for care homes and hostels electricity consumption indicators (SQ21-type buildings). Several buildings have been identified as being outside the expected pattern for different reasons. Betty Ave B, Butterwick House, Cromwell House, Gumbrill House, Norfolk House and Ruppert House have been identified has having high electricity baseload, when compared with buildings of the same type.

From the discussion of results with Leicester energy management team it was found that identified WAA (Warden Assisted Accommodation) underwent an extensive lighting refurbishment in mid 2003 that finished in early 2004. This refurbishment increased significantly lighting levels but also electricity consumption in those buildings, which was probably the cause for the uncommon profile detected in the benchmarking exercise. It was also found that the lighting of the site large car park causes Butterwick House high electricity use overnight.

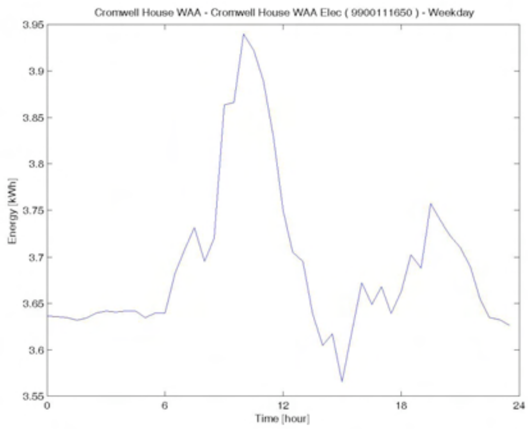
Other SQ21-type buildings were found to have high night-time consumption on weekdays and weekends, and high weekend consumption. However, Betty Ave B, Butterwick, Cromwell House, Gumbrill House, Norfolk House and Ruppert House, are the buildings that are significantly different from their peers. Their electricity load demand profiles are presented in Figure 67.



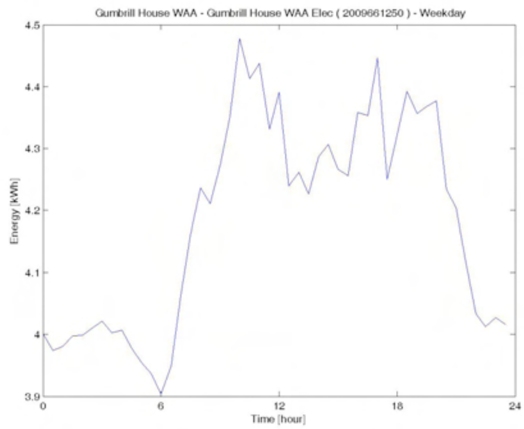
Betty Avenue B



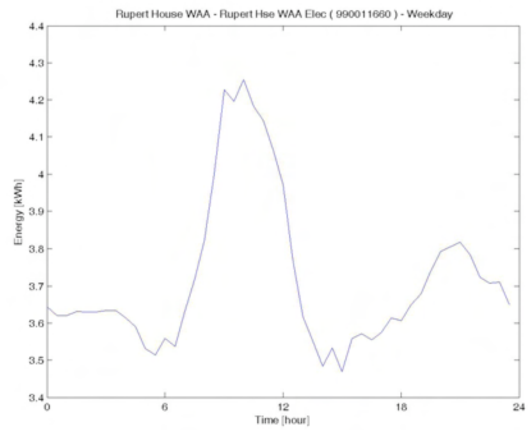
Butterwick House



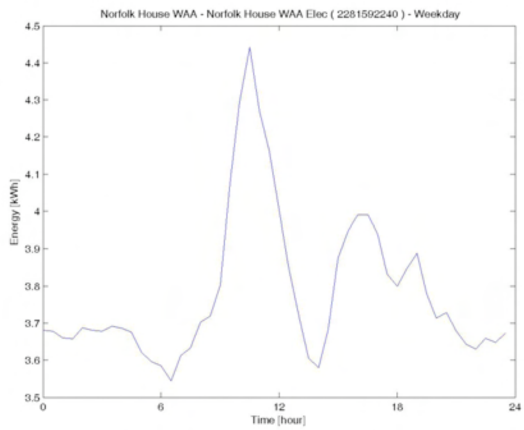
Cromwell House



Gumbrill House



Rupert House



Norfolk House

Figure 67. Betty Ave B, Butterwick House, Cromwell House, Gumbrill House, Norfolk House and Rupert House and electricity demand profiles – weekdays

9.3. Gas consumption benchmarking per building type

This section presents the gas consumption standardised results for the 6 building types. Note that gas consumption indicators include the non-weather related energy consumption (c_n), the relation between space heating needs and outside temperature (b_{1n}) and the outside temperature value below which space heating is turned on (b_3). These 3 indicators are not related to schedules and operating times, but to thermal performance of the buildings.

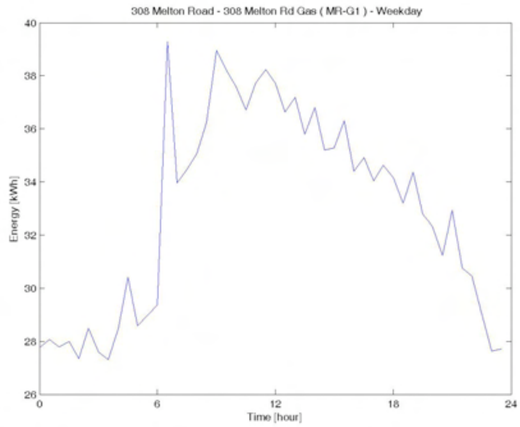
Table 32 presents the standard scores for indicators computed for Leicester City Council office and administrative buildings. From this table it is possible to identify the buildings with uncommon gas load demand profile characteristics, i.e. buildings with intensive high gas consumption, high baseload, high night-time and weekend gas consumption.

Table 32. Standard scores for gas indicators and CO-type buildings

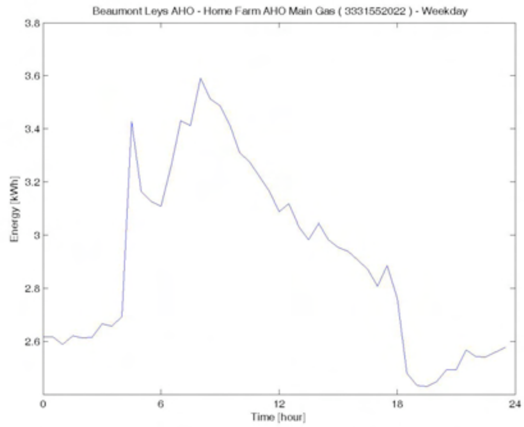
Standard Score	α_{D1}	α_{D2}	α_{D7}	α_{D8}	α_{W3}	c_n	b_{1n}	b_3
308 Melton Rd Gas	1.32	1.25	0.80	0.41	0.57	1.23	0.68	-0.03
16 New Walk Gas	-0.74	-0.89	-0.67	1.00	-2.27	0.06	-1.09	-1.05
47 New Walk Gas	-1.23	-1.03	-1.31	-0.61	-0.42	1.65	-1.69	1.02
Attenborough House Gas	0.63	0.84	0.62	0.07	0.76	n/a	n/a	n/a
Home Farm AHO Main Gas	1.20	1.26	1.04	0.57	0.92	-0.89	0.72	2.49
Charnwood AHO Main Gas	-0.62	-0.59	-0.79	-1.52	0.57	-1.05	0.17	0.88
Energy Office Gas	-0.96	-0.68	-1.07	-1.25	-0.37	-0.96	-0.41	-0.27
Home Improvement Agy Gas	1.58	1.39	1.37	0.98	0.64	0.02	0.64	0.16
Humberstone AHO Main Gas	-0.34	-0.91	0.15	-0.50	0.79	-0.89	2.50	0.03
Marlborough House Gas	-0.88	-1.07	-1.37	1.62	-2.21	0.17	-1.24	-1.65
New Parks AHO Gas	0.13	0.56	0.51	0.15	0.56	n/a	n/a	n/a
New Walk B Block Gas	-0.68	-0.81	-1.09	-0.73	-0.98	-0.72	-0.31	0.26
Phoenix House Gas	-0.53	-0.75	0.09	0.54	-0.84	-0.52	-0.25	0.09
Rowsley St AHO Gas	-1.09	-0.86	-1.35	-2.15	0.44	-0.48	0.39	0.38
Saffron AHO Gas	-0.61	-0.64	1.09	1.12	0.41	-0.23	0.27	-0.31
Sth Braunstone AHO Gas	1.26	1.41	1.04	0.68	0.59	1.99	0.65	-1.37
St Marks AHO Main Gas	1.82	1.57	1.29	0.69	0.81	n/a	n/a	n/a
Tudor Centre Gas	0.31	0.43	0.48	0.04	0.77	1.01	-0.88	-0.87
Town Hall Gas	-0.58	-0.47	-0.84	-1.01	-0.75	-0.59	-0.17	0.24

According to these results it can be said that AHO (Area Housing Offices) buildings are not very well controlled. According to Leicester energy management team AHO have a recurrent tendency for having automatic heating controls being overridden by building occupants. Using the indicators: gas is used intensively, and consumption sometime occurs outside the occupancy hours, i.e. overnight.

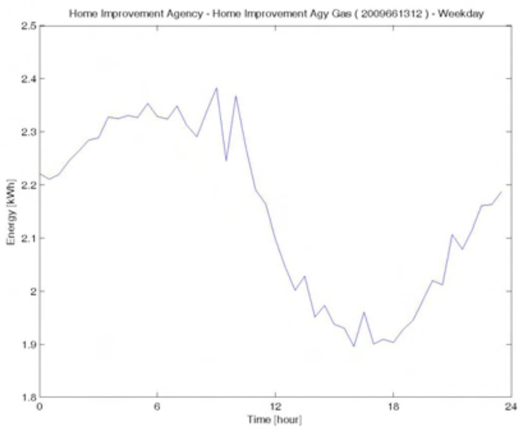
The Figure 68 presents the gas demand profiles for 308 Melton Road, Home Farm AHO, Home Improvement Agency, Saffron AHO, South Braunstone AHO and St. Marks AHO buildings. These are the buildings with potentially high gas use, load factor and overnight consumption, as identified by the indicators.



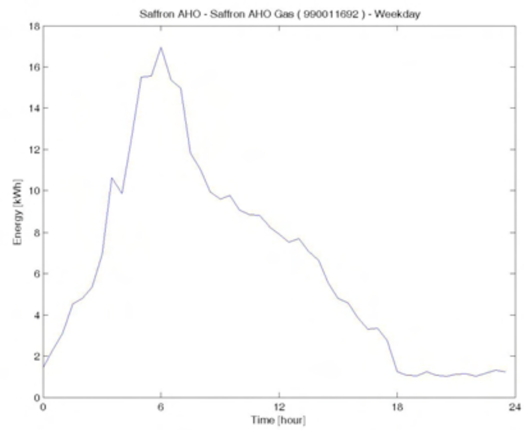
308 Melton Road



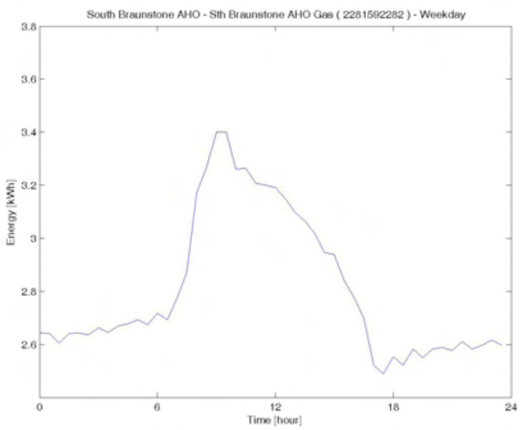
Home Farm AHO



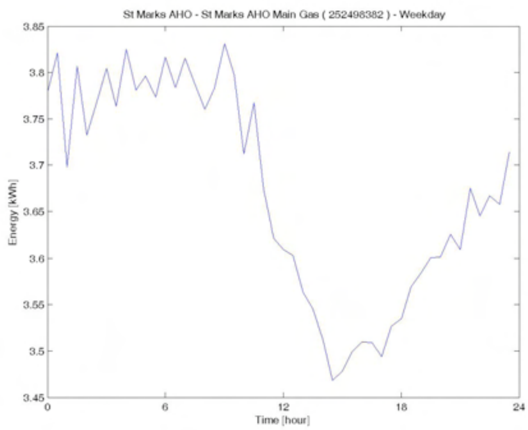
Home Improvement Agency



Saffron AHO

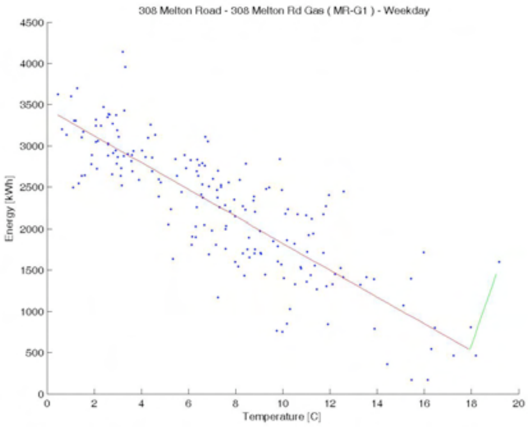


South Braunstone AHO

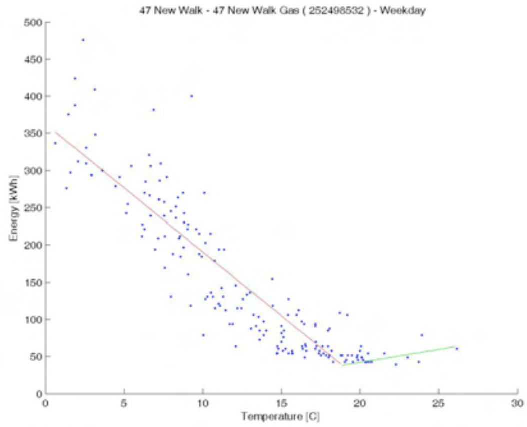


St. Marks AHO

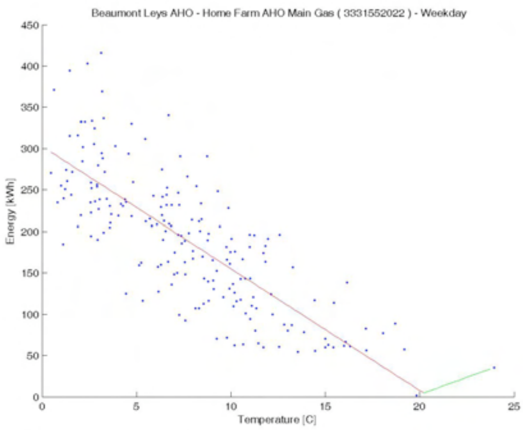
Figure 68. 308 Melton Road, Home Farm AHO, Home Improvement Agency, Saffron AHO, South Braunstone and St. Marks gas demand profiles – weekdays



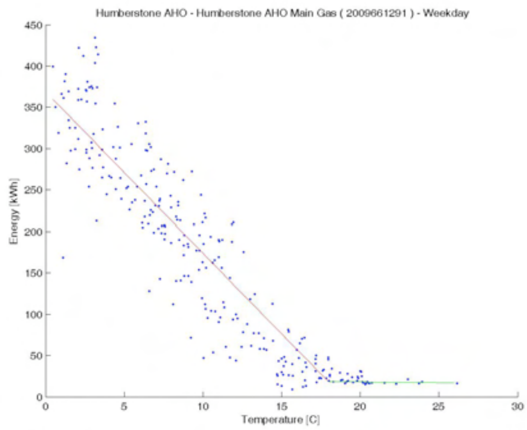
308 Melton Road



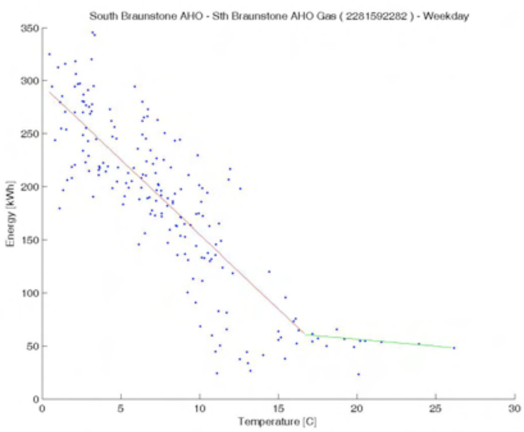
47 New Walk



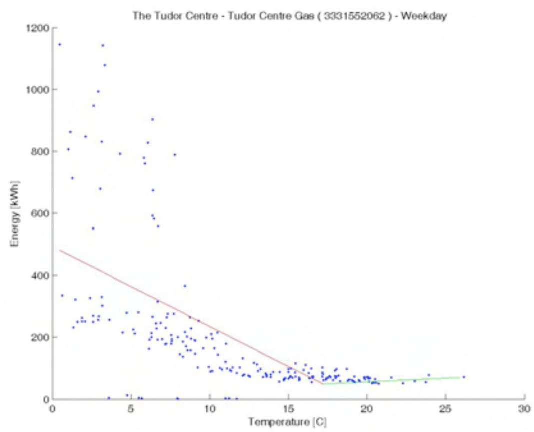
Home Farm AHO



Humberstone AHO



South Braunstone AHO



The Tudor Centre

Figure 69. 308 Melton Road, 47 New Walk, Home Farm, Humberstone AHO, South Braunstone AHO and Tudor Centre gas regression plots

Concerning the IMT model parameters standardisation, it was possible to detect buildings with scores above 1.00. 308 Melton Road, 47 New Walk, South Braunstone AHO and Tudor Centre were identified for having high fixed gas consumption, i.e. gas consumption for hot water and catering. Humberstone AHO was identified because gas demand increases more than average per unit of temperature decrease normalised by total gas usage. 47 New Walk and Home Farm AHO were identified because of high change-point temperature score. The IMT model plots for 308 Melton Road, 47 New Walk, Home Farm AHO, Humberstone AHO, South Braunstone AHO and Tudor Centre are presented in Figure 69.

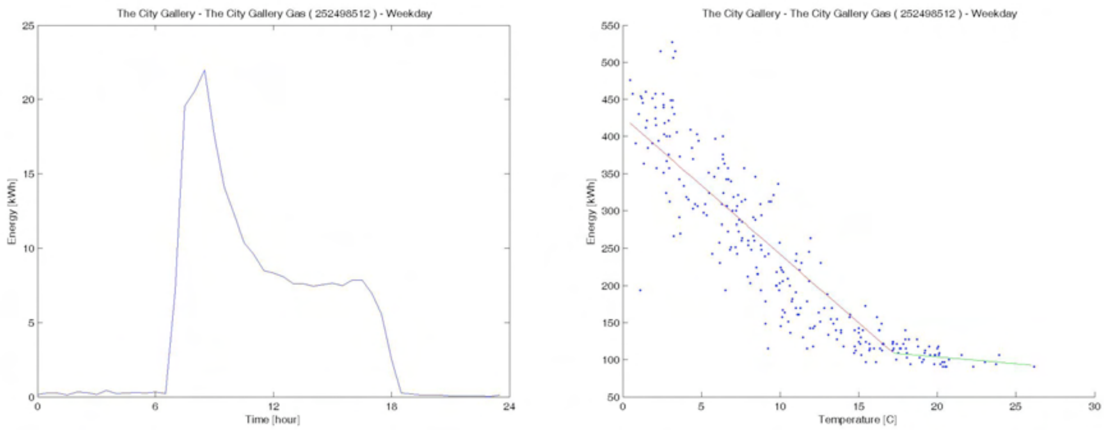
Note that non-weather related gas consumption (c_n) and the building with high gas use per temperature variation (b_{1n}) are not immediately identifiable from the plots because c_n and b_{1n} have been normalised by total energy use. However, the change-point temperatures (b_3) can be directly perceived from the IMT model plots.

Table 33 presents the standard scores for HL1-type buildings gas consumption. New Walk Museum and Central Library have been highlighted for high load factor and baseload. Belgrave library was identified for high night-time gas consumption on weekdays and weekends. New Walk Museum and Westcotes Library have been also identified for high weekend gas consumption. The City Gallery was the only building identified having high non-weather related use and high gas consumption dependency from outside temperature. However, from Figure 70 no uncommon profiles characteristics are visible.

Visually the City Gallery profile and regression plots are normal, and there is no evidence that this building could have uncommonly high non-weather related gas use (c_n) and dependency on outside temperature (b_{1n}) normalised by annual gas consumption. Nevertheless, the indicators calculated for City Gallery gas consumption found that this building is different from other HL1-type buildings in the group. This building uses a lot more hot water than other buildings in the group.

Table 33. Standard scores for gas indicators and HL1-type buildings

Standard Score	α_{D1}	α_{D2}	α_{D7}	α_{D8}	α_{W3}	c_n	b_{1n}	b_3
New Walk Museum Gas	1.74	1.50	0.98	0.96	1.05	-0.51	0.62	0.96
The City Gallery Gas	-1.37	-0.85	-1.37	-1.40	-0.86	2.17	1.43	0.42
Aylestone Library Gas	0.36	1.00	0.03	0.00	0.97	0.28	0.13	0.54
Belgrave Library Gas	0.16	-0.61	1.30	1.43	-0.70	-0.40	-0.09	0.06
Central Library Gas	1.25	1.43	0.97	0.86	-0.10	n/a	n/a	n/a
Reference Library Gas	-0.46	-0.77	-0.96	-0.87	-1.15	-0.46	-1.43	-1.47
Evington Library Gas	-0.33	-0.44	-1.14	-1.23	0.70	n/a	n/a	n/a
Southfields Library Gas	-0.44	-0.54	-0.27	-0.01	-1.16	-0.46	-1.13	-1.34
Westcotes Library Gas	-0.93	-0.72	0.45	0.27	1.25	-0.61	0.47	0.82



Load demand profile IMT model regression

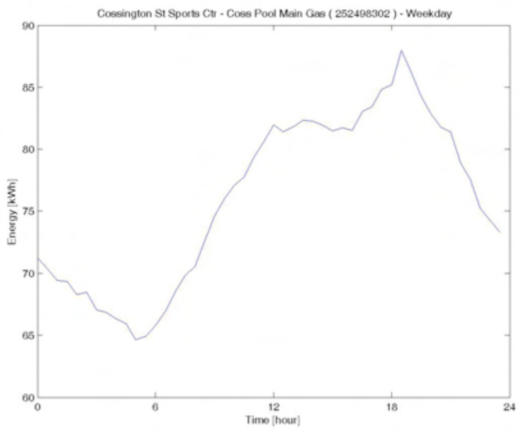
Figure 70. The City Gallery gas profile and regression plots

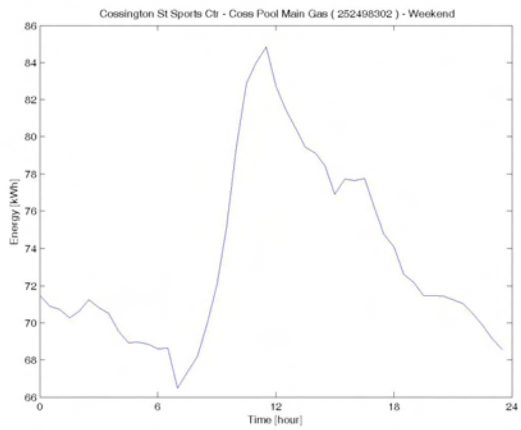
Table 34 presents the scores for gas consumption from Leisure centres (HL3-type buildings). The standardisation and benchmarking enabled the identification of a building with high baseload, and high night-time consumption on weekdays and on weekends (α_{D2}, α_{D7} and α_{D8}).

Table 34. Standard scores for gas indicators and HL3-type buildings

Standard Score	α_{D1}	α_{D2}	α_{D7}	α_{D8}	α_{W3}	c_n	b_{1n}	b_3
Aylestone Les Main Gas	0.25	0.04	0.13	-0.09	0.57	-0.03	0.15	-0.82
New Parks Les Gas	0.28	-0.13	-0.08	-0.46	0.74	-0.26	0.58	0.70
Spence St Hall Main Gas	-1.76	-1.58	-1.61	-1.27	-1.74	n/a	n/a	n/a
Coss Pool Main Gas	0.65	1.07	1.08	1.41	0.16	-1.26	0.40	0.48
Spence St Pool Gas	0.58	0.60	0.51	0.41	0.26	0.01	0.63	0.95

The following figure presents Cossington Pool gas load demand profile for weekdays and weekends. This is an old Victorian swimming pool, while others are modern swimming pools, and therefore it is expected to have higher thermal losses through the building envelope.





Weekdays Weekend

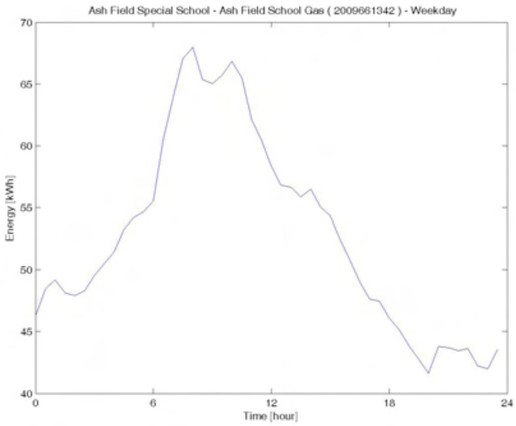
Figure 71. Cossington Pool gas demand profile – weekdays and weekend

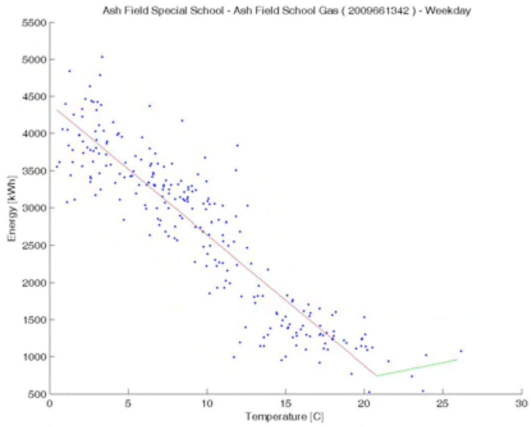
Table 35 presents the standard scores for gas consumption on school buildings (SE-type buildings). The benchmarking exercise allowed the identification of two schools with intensive gas use, high baseload and night-time use on weekdays: Ash Field Special School and Millgate Centre. These are both special schools with higher requirements in terms of occupancy hours and space heating than other schools. Other two schools were identified for high non-weather related gas use: Heatherbrook and Judgemeadow.

Table 35. Standard scores for gas indicators and SE-type buildings

Standard Score	α_{D1}	α_{D2}	α_{D7}	α_{D8}	α_{W3}	c_n	b_{1n}	b_3
Lansdowne Pre School Gas	0.48	0.50	-0.12	0.70	-0.02	-0.98	-1.22	0.12
Catherine Jnr School Gas	-1.42	-0.77	-1.53	-1.74	-1.68	n/a	n/a	n/a
Heatherbrook Sch Gas	-0.37	-0.52	-1.02	-0.47	0.79	1.11	0.83	0.02
Scraptoft Valley Prim. Gas	-1.06	-0.77	0.11	0.20	0.61	-1.27	-0.66	-0.30
Thurnby Lodge Primary Gas	-0.26	-0.58	0.29	1.40	-1.02	-0.79	-1.17	-0.13
Whitehall Sch Main Gas	0.22	0.62	0.84	0.76	0.11	0.80	0.79	-0.11
Judgemeadow CC Gas	0.38	-0.70	0.36	-0.77	-0.23	1.60	-1.05	-2.13
New College Main Gas	-1.24	-0.73	-1.50	-1.14	-1.43	n/a	n/a	n/a
Ash Field School Gas	1.82	2.07	1.55	0.84	0.59	0.27	1.19	1.73
Millgate Centre Main Gas	1.16	1.41	1.02	0.84	0.89	-0.34	0.55	0.31
Nether Hall School Gas	0.28	-0.52	0.01	-0.60	1.38	-0.42	0.75	0.49

Ash Field Special School was again identified, this turn for having high gas use dependency on temperature, and high change-point temperature. Figure 72 presents the gas load demand profile and IMT regression plots for Ash Field Special School gas consumption, in which no problems are clearly visible.





Load demand profile | IMT model regression

Figure 72. Ash Field Special School gas profile and regression plots

Table 36 presents the standardisation of gas consumption indicators for community buildings (SQ10-type buildings). The scores enabled the benchmarking of similar type of buildings, and allowed the identification of specific buildings with uncommon gas consumption profile characteristics. Coleman NC, Lansdowne NC and Netherhall NC were identified due to intensive gas usage, high baseload and/or out-of-hours gas consumption. Lansdowne NC was also identified due to excessive non-weather related gas use. St. Saviours was identified because of the dependency of gas use from outside temperature.

Table 36. Standard scores for gas indicators and SQ10-type buildings

Standard Score	α_{D1}	α_{D2}	α_{D7}	α_{D8}	α_{W3}	c_n	b_{1n}	b_3
Coss Fam Centre Gas	-1.37	-0.71	-1.15	0.79	-2.09	n/a	n/a	n/a
Belgrave Neigh. Cent Gas	-0.13	-0.75	-0.21	-0.45	0.41	0.45	0.40	-0.12
Braunstone Oak NC Gas	-0.50	-0.70	-1.06	-1.41	-0.62	n/a	n/a	n/a
Coleman Neigh Centre Gas	0.10	1.10	0.52	0.36	0.70	0.12	0.55	0.16
Lansdowne Neigh Cent Gas	1.22	1.42	0.67	0.23	0.78	1.68	-0.10	-0.21
Netherhall Neigh Cent Gas	1.89	1.08	1.25	1.32	0.63	-1.02	0.01	0.05
St Saviours NC Gas	-0.43	-0.65	-1.07	-1.40	0.62	-0.33	1.01	1.62
Welford House Gas	-0.57	-0.79	1.04	0.56	-0.44	-0.90	-1.87	-1.51

From the discussion of results with Leicester energy management team it was found that Netherhall NC provides catering services 7-days a week for poor people. This might be the cause of excessive energy use when compared with other NC.

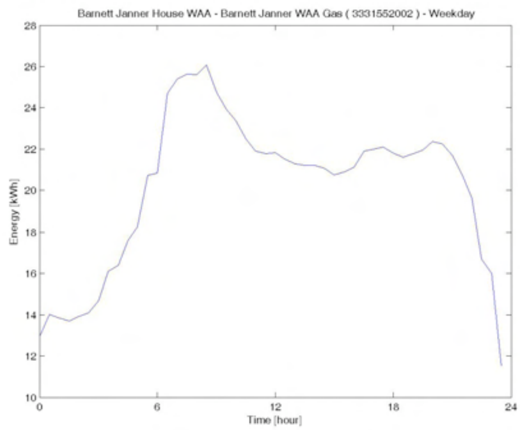
The following table presents the benchmarking of gas consumption from care homes and hostels (SQ21-type buildings). In Table 37 buildings that have been highlighted for different reasons. Barnes Heath House, Cromwell House, Jackson House, Loughborough Road Hostel, 33 Lower Hastings Street and 38 Upper Tichbourne have been identified due to excessive gas usage, when compared with buildings of the same type.

Table 37. Standard scores for gas indicators and SQ21-type buildings

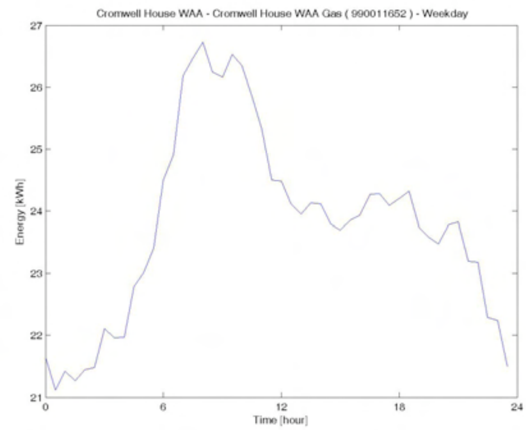
Standard Score	α_{D1}	α_{D2}	α_{D7}	α_{D8}	α_{W3}	c_n	b_{1n}	b_3
Abbey House EPH Gas	-1.05	-1.03	0.42	0.81	-2.14	0.58	0.36	0.13
Arbor House EPH Gas	-0.72	-2.22	-1.31	-1.01	1.20	0.24	0.88	0.85
Barnes Heath House Gas	1.19	0.73	1.28	1.24	0.69	1.36	0.23	-1.41
Barnett Janner WAA Gas	0.08	-0.23	-0.54	-0.67	0.21	-0.63	-0.47	0.20
Beatty Ave B Gas	-0.34	-0.84	-1.02	-1.13	0.13	0.48	0.74	0.06
Beaumanor Hostel Gas	-0.47	-1.59	-0.26	-0.44	0.48	0.74	-0.05	0.46
Bowder House WAA Gas	-0.37	0.07	0.22	0.22	0.21	1.30	1.31	-0.95
Bridges House WAA Gas	0.80	0.16	-0.58	-0.61	0.43	-2.11	-1.65	0.87
Butterwick Gas	-2.02	-1.17	-0.61	-0.66	0.35	-0.17	-0.16	-0.19
Cromwell House WAA Gas	1.00	0.95	0.54	0.53	0.40	0.63	0.24	-1.30
Dudley House WAA Gas	-0.68	-0.77	-0.65	-0.78	0.22	-0.10	0.06	0.04
Elizabeth House EPH Gas	0.42	0.59	0.61	0.67	0.15	1.23	1.54	-0.15
Fred.Thorpe WAA Gas	-1.03	-0.48	-0.62	-0.66	0.22	0.13	0.29	-0.04
Gumbrill House WAA Gas	0.77	0.56	0.39	0.30	0.36	-0.10	-0.27	-0.57
Helena Roberts WAA Gas	0.82	0.98	0.54	0.55	0.30	0.75	0.47	-1.20
Herrick Lodge EPH Gas	-1.76	-1.03	-2.63	-2.54	-3.86	n/a	n/a	n/a
Jackson House WAA Gas	1.02	0.75	0.36	0.22	0.47	-0.20	-0.11	-0.10
Lough Rd Hostel Gas	1.50	1.16	0.91	0.87	0.19	-0.81	-0.46	0.57
31 Lower Hastings St Gas	-2.27	-2.01	-2.53	-2.49	-1.15	-1.37	-1.36	0.30
33 Lower Hastings St Gas	1.40	1.09	0.92	0.82	0.41	-0.78	-0.55	0.31
Netherhall Childrens Gas	0.02	0.70	0.57	0.54	-1.55	0.28	-2.08	-2.06
Norfolk House WAA Gas	-0.37	0.29	-0.05	-0.22	0.09	-0.04	0.27	0.33
Nuffield House EPH Gas	0.04	0.62	1.47	1.55	0.00	-0.94	0.53	3.17
Pollard House WAA Gas	0.62	0.80	0.25	0.23	0.80	1.76	0.98	-1.51
Preston Lodge EPH Gas	-0.02	0.87	0.26	0.28	0.12	0.66	0.97	0.11
Rupert Hse WAA Gas	0.26	0.16	-0.37	-0.28	0.56	0.03	0.41	0.40
Tatlow Rd Comm Home Gas	0.13	0.93	0.65	0.73	0.23	-0.15	0.26	0.57
Thurncourt EPH Gas	-0.25	-1.02	0.38	0.56	-0.08	-0.07	0.55	1.06
38 Upper Titchbourne Gas	1.28	0.98	1.40	1.38	0.55	-2.69	-2.92	0.07

Figure 73 presents the gas load demand profiles for those buildings. The excessive gas consumption identified in building above can be do to 'normal' operational circumstances, or to energy wastage. The analysis the gas load demand plots is not enough to immediately detect the causes of excessive energy use, high baseloads or night-time consumption.

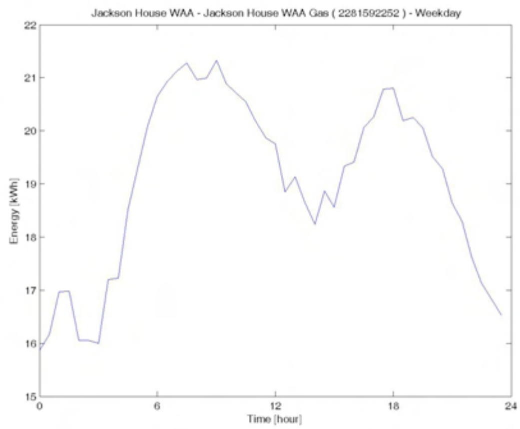
There were also buildings identified using IMT model parameters benchmarking. Barnes Heath House, Bower House, Elizabeth House and Pollard House have been highlighted for high non-weather related gas use. Nuffield House and Thurncourt Elderly People Home (EPH) were identified due to high change-point temperature. These regression plots for these 6 buildings are presented in Figure 74. From the regression plots gas consumption for SQ21-type buildings has a strong relationship with outside temperature. This is not the case for Thurncourt EPH, where the scatter is intense. However, and according to benchmarking of IMT model parameters, these buildings have uncommon demand profile characteristics, which could be indicative of potential saving opportunities. For 4 buildings these savings opportunities could derive from reducing gas use for water heating and cooking. For Nuffield House and Thurncourt EPH resetting the heating set point to a lower temperature could reduce gas consumption. These opportunities to save energy need to be confirmed on site.



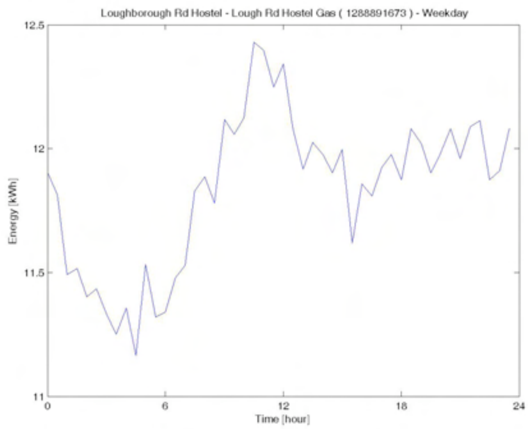
Barnes Heath House



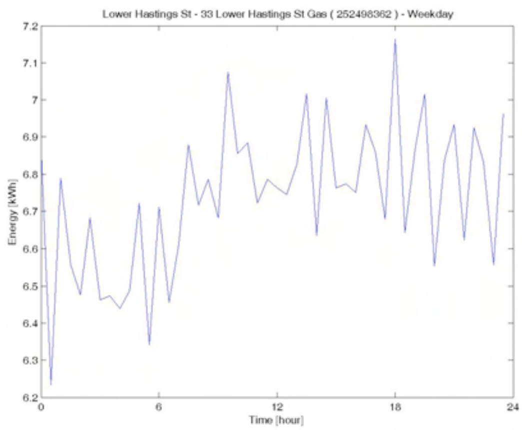
Cromwell House



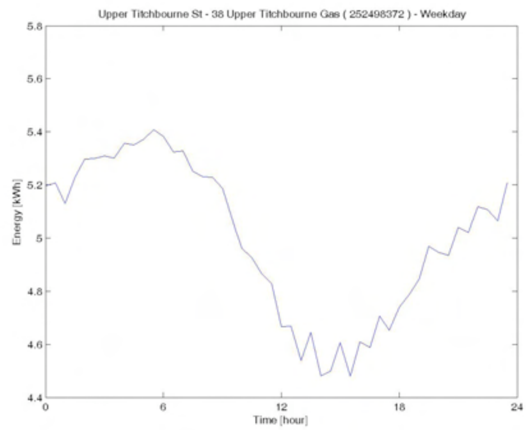
Jackson House



Loughborough Road Hostel

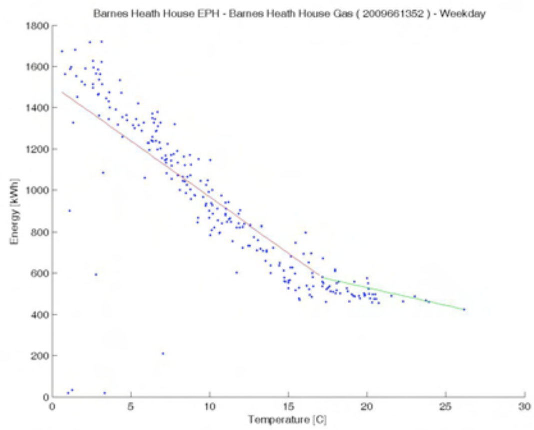


33 Lower Hastings Street

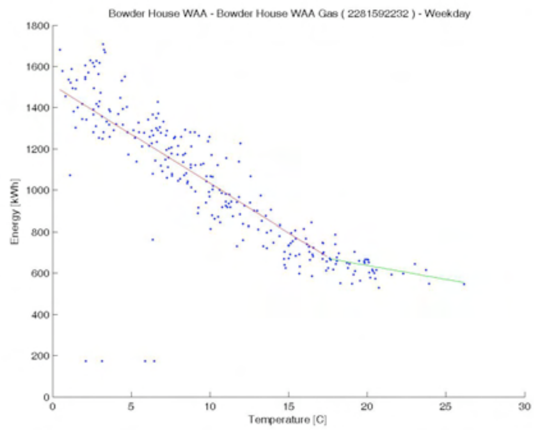


38 Upper Tichbourne

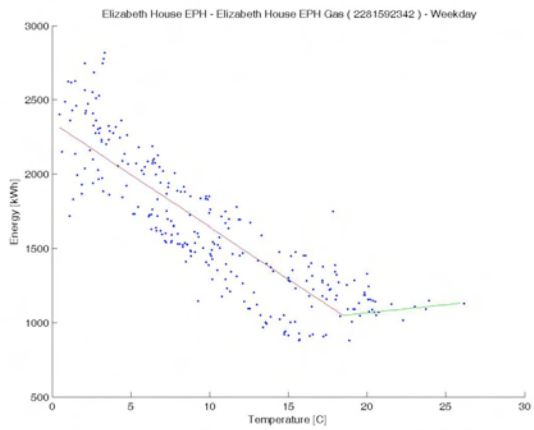
Figure 73. Barnes Heath House, Cromwell House, Jackson House, Loughborough Road Hostel, 33 Lower Hastings Street and 38 Upper Tichbourne gas profile plots



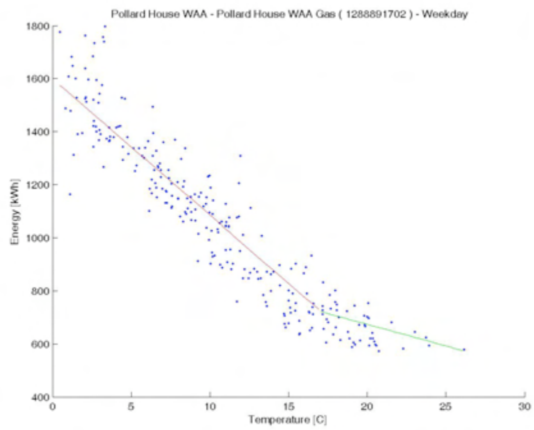
Barnes Heath House



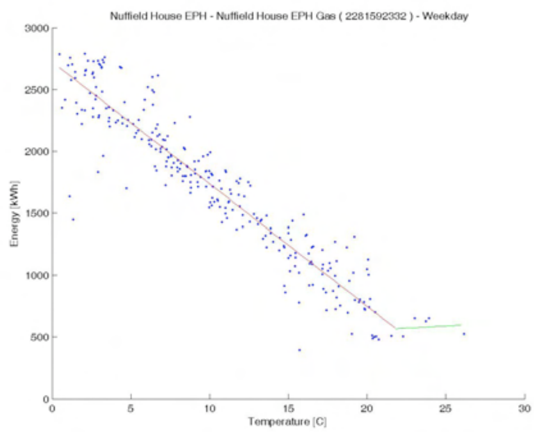
Bowder House



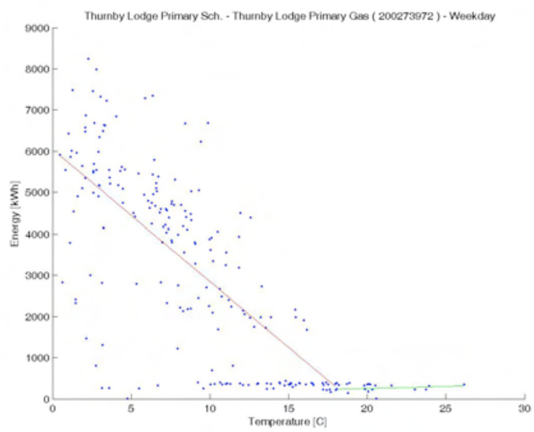
Elizabeth House



Pollard House



Nuffield House



Thurncourt EPH

Figure 74. Barnes Heath House, Bowder House, Elizabeth House, Pollard House Nuffield House and Thurncourt EPH gas regression plots

9.4. Chapter summary

This chapter demonstrated how it is possible to develop empirical benchmarks based on short time series energy data consumption analysis models, and on quantitative indicators. The load demand indicators and IMT model parameters, some of which were normalised, were applied to Leicester City Council data, in a unique benchmarking exercise. Although energy consumption data for some building types was limited, still it was possible to identify several buildings with uncommon profile characteristics.

The following figure presents a summary of results of the analysis of electricity consumption for all the selected buildings.

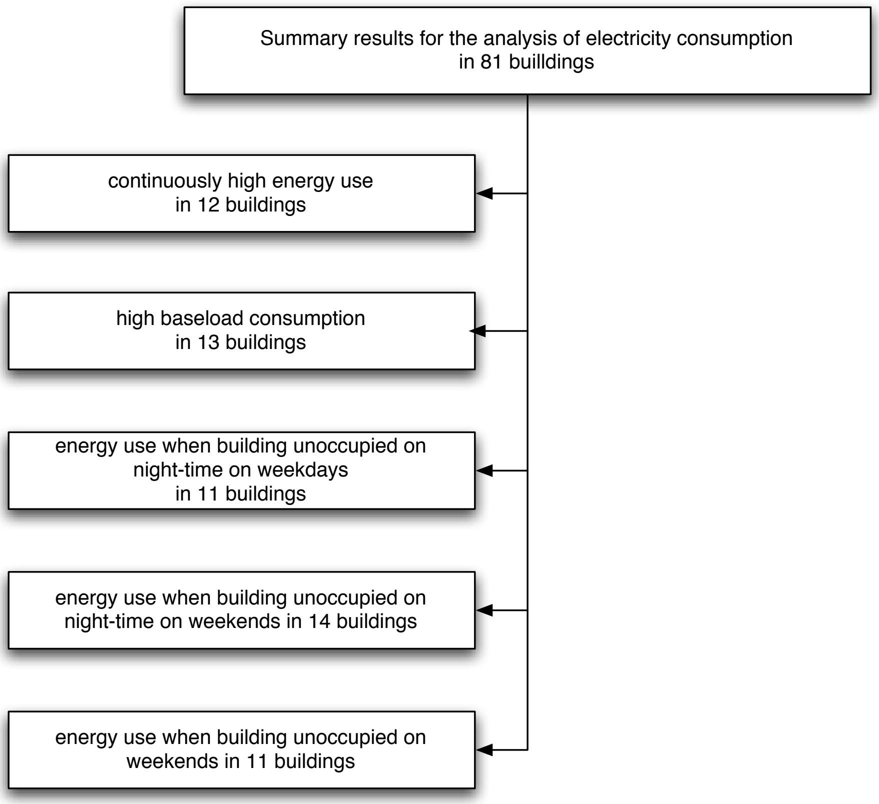


Figure 75. Summary of electricity analysis results

The benchmarking procedure allowed the identification of 12 buildings with continuously high electricity use (α_{D1}), 13 buildings with high baseloads (α_{D2}), 11 buildings with excessive electricity consumption overnight on weekdays (α_{D7}), 14 buildings with excessive electricity consumption overnight on weekends (α_{D8}) and 11 buildings with excessive electricity use on weekends (α_{W3}).

The following figure presents a summary of results of the analysis of gas consumption for the selected buildings. These results have been determined using the load shape indicators and regression coefficients.

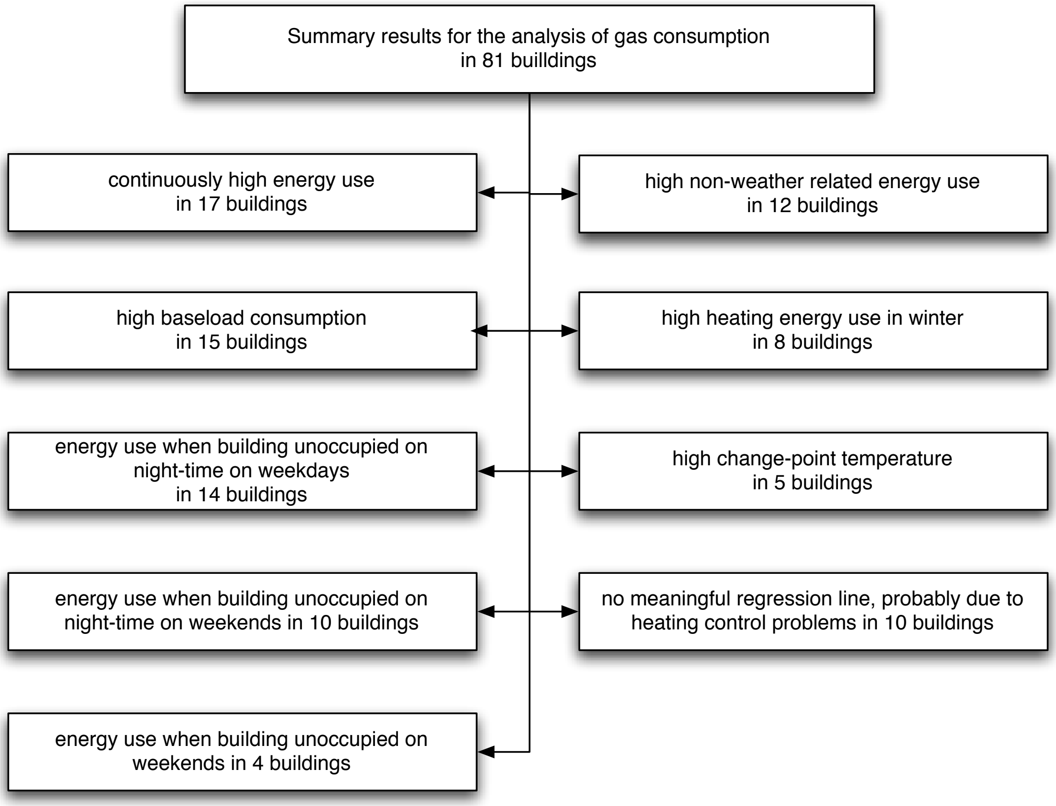


Figure 76. Summary of gas analysis results

The benchmarking procedure allowed the identification of 17 buildings with continuously high gas use (α_{D1}), 15 buildings with high gas baseload (α_{D2}), 14 building with excessive gas consumption overnight on weekdays (α_{D7}), 10 buildings with excessive gas consumption overnight on weekends (α_{D8}) and 4 buildings with excessive gas use on weekends (α_{W3}). Additionally, it was possible to identify 12 buildings for excessive non-weather related gas use, 8 building with high dependency of gas consumption on outside temperature and 5 buildings with high change-point temperatures. As presented in chapter 7, it was not possible to apply the IMT model to 10 buildings.

The benchmarking exercise allowed the comparison of indicators of similar buildings that were found to be related to normal building operation. For example Attenborough House was found to have intensive energy use, high baseload, and night-time consumption on weekdays. However, this building was found to have different uses from the other office buildings in the group.

The uncommon consumption profile characteristics detected using benchmarking may or may not be related to potential saving opportunities. Nevertheless, load demand and IMT model indicators supported the objective identification of existing deviations from the typical profile for buildings of the same type. This allows the prioritisation of buildings for further investigation, including the identification of specific profile characteristics that can be indicative of potential energy savings, and the possibility of automating the process.

Presenting and discussing the analysis results with Leicester energy management team attempted to establish the causes for uncommon features identified. However, this was only achieved for some buildings. In fact, energy managers confirmed that several of the features identified were known, but to many others they could not find or remember a cause. Therefore, one could speculate that these could be energy wastages that could be corrected.

Quantification of differences between profiles, and consequently the quantification of wastages and potential savings that could be introduced through correction actions was out of the scope of the research. The research aim was to develop an objective methodology to identify and benchmark buildings using primary meter short time series data, and this aim was accomplished. Further research is needed in order to refine the developed benchmarking methodology in order to extend its applicability to other buildings types and to all energy users.

The following section presents the main findings of this research in contrast with existing conventional approaches. Contributions to knowledge, advantages and shortcomings of the benchmarking framework tested under the current study are discussed in detail, including the presentation of the opportunities for further research.

Chapter 10. Discussion and further research

This research presents a novel method of characterising quantitatively building consumption profiles using a set of indicators that are applied to historical records of electricity and gas half-hourly data. Some of these indicators were used to investigate electricity and gas consumption profiles for different municipal building types using Leicester City Council metering database. The application of indicators to benchmark buildings of a similar type allowed the identification of bias in consumption profiles characteristics, which may be indicative of potential energy savings opportunities from undetected wastage.

This thesis is original because it uses real primary energy meter short time series data from 81 municipal buildings, and a novel metric to characterise electricity and gas consumption and benchmarking for the comparison of demand profiles. The metric based on load demand profile shape indicators has never been applied to building energy management. The IMT building energy signatures, in the past used to set baselines and calculate energy savings from energy efficiency measures, were now applied to conduct benchmarking within buildings of a same type.

10.1. The metric and the indicators in context

The initial chapters of this thesis presented the state of the art in terms of data acquisition and data analysis (chapter 2) the best practice in terms of visualisation techniques and manual diagnostics using short time series data (chapter 3) and a review of current practice in municipal building energy management (chapter 4).

In chapter 2 the need for improved automatic diagnostics and expert interpretation of short time series data, namely data generated by smart metering systems that are mostly primary meters, was identified. It is expected an increasing availability of short time series energy consumption data, which can be used to understand the past and present building energy consumption profiles. This data can also be used to identify and support the implementation of opportunities for reducing energy demand and carbon emissions. The literature review presented several valid approaches to building diagnostics but none was specific to performing automated building energy diagnostics using historical records of primary energy meter short time series data.

Visualisation techniques offer a valid approach to analyse short time series data, particularly advanced visualisation techniques that incorporate graphical indices, as presented in chapter 3. 3D, 2D, line plots and load demand profiles visualisation techniques are useful for identifying excessive consumption, occurrence of untypical high or low consumption, general variation of demand patterns, determination of occupancy hours, baseload and demand on different periods of the day. The integration of percentiles analysis – graphical indices – in the plots enhances the visualisation capabilities, and provides insight on profile variations on holidays and breaks, difference between weekdays and weekends, and consistency of building operation over a period of time, typically a year. An important limitation of visualisation is that its effectiveness for manual diagnosis using short time series data is strongly dependent to the experience of the analyst.

From the survey of European municipal energy managers (chapter 4) it was found that energy managers are using conventional techniques, and therefore they are not trained in energy analysis. For instance, no reference was found in the replies to the use of graphical indices. From the survey presented in chapter 4, it was also found that energy managers use mostly benchmarks on an annual basis. In fact, they prefer benchmarking, simple visualisation techniques, and comparisons between past and current consumption. In the survey there are a few references to the use of regression models for assessing building performance, and there was only one reference to the use of half hourly electricity data and demand profiles.

The approach proposed in the current work uses an increasingly available resource – primary meter short time series building energy consumption data. The metric proposed in this thesis goes beyond the advanced visualisation techniques presented in chapter 3 because it eliminates the subjectivity, and the need for having an energy manager trained in advanced visualisation techniques for energy consumption analysis. Nevertheless, visualisation with graphical indices can provide additional information to load demand shape profile indicators and IMT regression coefficients calculated for the annual mean profile. For instance, they can provide information about the variations of the demand profile over the year.

The proposed approach is aligned with energy managers' requirements for objective interpretation of energy consumption data analysis, and to the use of benchmarking in order to automate the identification of potential energy saving opportunities. The indicators metric can be applied to assess different demand profile characteristics: non-weather related energy use, dependency of energy use on outside temperature, heating set-point temperature, intensity of energy use, baseload consumption, energy use when building unoccupied on night-time on weekdays and on weekends.

This thesis resulted in what can be understood as a semi-automated building energy diagnostics tool. The calculation of indicators, the benchmarking analysis and the identification of the buildings can be fully automated in the future. However the identification of the causes of uncommon characteristics of the building energy consumption profiles requires information only available though a discussion of results with energy manager or by conducting a site survey.

10.2. Annual performance indicators and the new energy indicators

Chapter 5 included a presentation of Leicester City Council buildings to be analysed. NPI indicators and comparison against UK benchmarks was conducted for electricity and gas consumption for the 81 selected buildings. The results were presented in Table 7 for electricity consumption and in Table 8 for gas consumption.

Due to lack of floor area data availability, it was only possible to calculate electricity NPI for 64 buildings, corresponding to a success rate of 79% (64 in a total of 81). Comparing the NPI calculated with UK benchmarks resulted in the identification of 36 buildings, corresponding to 56% of the number of building for which it was possible to calculate electricity NPI.

Table 38 compares electricity NPI results with the standard scores results presented earlier in Table 26, Table 27, Table 28, Table 29, Table 30 and Table 31. It was possible to calculate electricity load demand shape indicators for the 81 buildings (success rate 100%), and the application of standard scores resulted in the identification of 26 buildings, 32% of the total buildings analysed. About 11 buildings were identified both by the NPI and by at least one load demand shape indicator.

Table 38. Comparison of electricity NPI and Standard Score results

Meters	NPI	Standard Scores				
	Actual % of Typical	α_{D1}	α_{D2}	α_{D7}	α_{D8}	α_{W3}
16 New Walk Elec	85%	0.25	-0.85	-0.95	0.71	-1.15
308 Melton Rd Elec	n/a	0.08	0.24	0.35	-1.73	1.20
31 Lower Hastings St Elec	81%	0.15	-1.56	-0.47	-0.84	1.47
33 Lower Hastings St Elec	281%	-0.23	-0.53	-0.27	-0.30	-0.01
38 Upper Titchbourne Elec	65%	0.26	-0.20	0.43	0.35	0.14
47 New Walk Elec	104%	-1.04	-0.96	-1.08	0.97	-1.44
Abbey House EPH Elec	144%	-0.52	-0.24	-0.28	-0.26	-0.48
Arbor House EPH Elec	145%	-0.35	-0.37	-0.57	-0.64	-0.01
Ash Field School Elec	137%	2.15	1.78	2.17	1.38	0.21
Attenborough House Elec	94%	2.60	2.24	2.30	-0.32	2.36
Aylestone Les Main Elec kWh	183%	0.42	0.40	0.52	0.42	0.70
Aylestone Library Elec	70%	-2.19	0.15	-0.07	-1.01	1.90
Barnes Heath House Elec	161%	0.95	0.33	1.63	1.46	1.47
Barnett Janner WAA Elec	n/a	0.19	0.58	-0.13	-0.30	0.77
Beatty Ave B Elec	n/a	1.84	1.71	1.23	1.11	0.18
Beaumanor Hostel Elec	72%	-1.51	-2.50	-2.68	-2.67	-0.65
Belgrave Library Elec	175%	0.13	-0.63	-0.49	-0.38	-0.50
Belgrave Neigh. Cent Elec	317%	1.05	-0.05	0.08	-1.11	0.89
Bowder House WAA Elec	n/a	-0.23	1.10	0.68	0.82	-0.49
Braunstone Oak NC Elec	162%	0.67	0.14	-0.55	0.18	-0.64
Bridges House WAA Elec	n/a	-0.67	-0.73	-0.93	-1.18	0.80
Butterwick Elec	57%	1.18	0.55	1.64	1.41	0.95
Catherine Jnr School Elec	146%	-0.46	0.55	0.08	-0.03	0.63
Central Library Elec kWh	203%	0.86	-0.38	-0.01	-0.02	-0.51
Charnwood AHO Main Elec	57%	-1.48	-0.40	-0.56	0.21	-0.66
Coleman Neigh Cent Elec	189%	0.65	0.58	-0.25	-0.48	0.07
Coss Fam Centre Elec	27%	-1.69	-1.30	-1.17	0.79	-1.83
Coss Pool Elec kWh	92%	0.63	0.56	0.57	0.66	0.33
Cromwell House WAA Elec	n/a	1.73	1.80	1.16	1.03	1.81
Dudley House WAA Elec	n/a	0.10	-0.19	-0.60	-0.74	0.40
Elizabeth House EPH Elec	133%	-0.25	0.24	-0.09	-0.20	0.39
Energy Office Elec	117%	0.00	0.19	0.35	-0.15	0.11
Evington Library Elec	22%	-0.28	-0.61	-0.75	-1.06	0.07
Fred.Thorpe WAA Elec	n/a	0.61	-0.50	0.01	-0.14	0.47
Gumbrill House WAA Elec	n/a	1.09	1.33	0.86	0.71	0.50
Heatherbrook Sch Elec	146%	-0.84	-0.52	-0.36	1.00	0.00
Helena Roberts WAA Elec	n/a	-1.81	0.23	-0.60	-0.05	-2.06
Herrick Lodge EPH Elec	113%	-0.62	-0.55	-1.21	-0.77	-2.10
Home Farm AHO Main Elec	96%	-1.13	-1.38	-1.49	-2.16	-0.93
Home Improvement Agy Elec	12%	-0.63	-0.13	-0.26	1.22	-0.53
Humberstone AHO Main Elec	59%	-0.50	-0.63	-0.66	-1.07	-0.05
Jackson House WAA Elec	n/a	0.50	0.09	-0.46	-0.59	0.25
Judgemeadow CC Elec kWh	119%	-0.01	-1.06	-1.02	-1.47	-0.85
Lansdowne Neigh Cent Elec	44%	-1.28	0.00	-0.51	-1.29	0.08
Lansdowne Pre School Elec	55%	-0.58	-0.75	-1.06	-0.57	-0.86
Lough Rd Hostel Elec	n/a	0.27	-0.16	0.68	0.67	-0.43
Marlborough House Elec kWh	43%	-0.24	-1.18	-1.29	0.55	-1.49
Millgate Centre Elec kWh	219%	1.33	1.24	0.71	-0.75	1.10
Nether Hall School Elec	n/a	0.26	0.74	0.82	-0.87	1.75
Netherhall Childrens Elec	127%	-1.81	-0.71	-0.45	-0.53	0.47
Netherhall Neigh Cent Elec	143%	-0.28	1.81	0.68	0.05	0.92
New College Main Elec kWh	46%	0.45	0.51	0.24	-1.01	0.85
New Parks AHO Elec	132%	0.29	0.65	0.67	0.92	0.36
New Parks Les Main Elec kWh	140%	0.14	0.59	0.48	0.43	0.43
New Walk B Block Elec kWh	96%	1.80	1.83	1.66	0.37	1.29
New Walk Museum Elec kWh	105%	1.07	2.55	2.45	1.88	1.33
Norfolk House WAA Elec	n/a	0.80	1.36	0.99	0.82	0.77
Nuffield House EPH Elec	138%	-1.02	-1.37	-1.08	-0.98	-0.57
Phoenix House Elec kWh	43%	0.22	-1.00	-0.72	-0.81	-0.58
Pollard House WAA Elec	n/a	-0.31	-0.29	-1.24	-1.33	0.10
Preston Lodge EPH Elec	155%	-0.98	-1.13	-0.78	-0.53	-0.37
Reference Library Elec	186%	0.88	-0.22	0.36	0.54	-0.43
Rowsley St AHO Elec	47%	-0.51	0.67	0.47	0.71	0.22
Rupert Hse WAA Elec	n/a	1.05	1.32	1.07	1.21	-0.46
Saffron AHO Elec	66%	-0.36	-0.71	-0.44	0.06	-0.32
Scraptoft Valley Prim. Elec	118%	-0.53	-0.72	0.27	1.32	-0.41
Southfields Library Elec	236%	0.07	0.13	-0.06	1.04	-1.05
Spence St Hall Main Elec	n/a	-1.76	-1.77	-1.77	-1.77	-1.77
Spence St Pool Elec kWh	83%	0.56	0.22	0.20	0.26	0.31
St Marks AHO Main Elec	89%	-0.56	0.03	-0.16	-1.41	0.42
St Saviours NC Elec	404%	0.27	-1.29	2.10	1.80	1.10
Sth Braunstone AHO Elec	107%	-0.30	-0.32	0.10	0.91	-0.15
Tatlow Rd Comm Home Elec	181%	0.25	0.91	0.89	1.31	-2.22
The City Gallery Elec	141%	-0.66	-0.48	-0.70	-0.88	0.10
Thurnby Lodge Primary Elec	76%	-1.19	-1.16	-1.01	0.50	-1.30
Thurncourt EPH Elec	151%	-1.24	-0.34	0.60	1.14	-1.08
Town Hall Elec kWh	38%	1.30	1.07	1.05	0.14	0.78
Tudor Centre Elec	66%	0.20	0.63	0.66	0.89	0.47
Welford House Elec kWh	365%	0.61	0.11	-0.38	0.05	-0.60
Westcotes Library Elec	67%	0.12	-0.51	-0.74	-0.11	-0.91
Whitehall Sch Main Elec	101%	-0.61	-0.60	-0.84	0.50	-1.12

Table 39. Comparison of gas NPI and Standard Score results

Meters	NPI	Standard Scores							
	Actual % of Typical	α_{D1}	α_{D2}	α_{D7}	α_{D6}	α_{W3}	c_n	b_{1n}	b_3
16 New Walk Gas	53%	-0.74	-0.89	-0.67	1.00	-2.27	0.06	-1.09	-1.05
308 Melton Rd Gas	n/a	1.32	1.25	0.80	0.41	0.57	1.23	0.68	-0.03
31 Lower Hastings St Gas	43%	-2.27	-2.01	-2.53	-2.49	-1.15	-1.37	-1.36	0.30
33 Lower Hastings St Gas	96%	1.40	1.09	0.92	0.82	0.41	-0.78	-0.55	0.31
38 Upper Titchbourne Gas	39%	1.28	0.98	1.40	1.38	0.55	-2.69	-2.92	0.07
47 New Walk Gas	87%	-1.23	-1.03	-1.31	-0.61	-0.42	1.85	-1.69	1.02
Abbey House EPH Gas	96%	-1.05	-1.03	0.42	0.81	-2.14	0.58	0.36	0.13
Arbor House EPH Gas	76%	-0.72	-2.22	-1.31	-1.01	1.20	0.24	0.88	0.85
Ash Field School Gas	171%	1.82	2.07	1.55	0.84	0.59	0.27	1.19	1.73
Attenborough House Gas	n/a	0.63	0.84	0.62	0.07	0.76	n/a	n/a	n/a
Aylestone Les Main Gas	81%	0.25	0.04	0.13	-0.09	0.57	-0.03	0.15	-0.82
Aylestone Library Gas	137%	0.36	1.00	0.03	0.00	0.97	0.28	0.13	0.54
Barnes Heath House Gas	87%	1.19	0.73	1.28	1.24	0.69	1.36	0.23	-1.41
Barnett Janner WAA Gas	n/a	0.08	-0.23	-0.54	-0.67	0.21	-0.63	-0.47	0.20
Beatty Ave B Gas	n/a	-0.34	-0.84	-1.02	-1.13	0.13	0.48	0.74	0.06
Beaumanor Hostel Gas	65%	-0.47	-1.59	-0.26	-0.44	0.48	0.74	-0.05	0.46
Belgrave Library Gas	102%	0.16	-0.61	1.30	1.43	-0.70	-0.40	-0.09	0.06
Belgrave Neigh. Cent Gas	136%	-0.13	-0.75	-0.21	-0.45	0.41	0.45	0.40	-0.12
Bowder House WAA Gas	n/a	-0.37	0.07	0.22	0.22	0.21	1.30	1.31	-0.95
Braunstone Oak NC Gas	n/a	-0.50	-0.70	-1.06	-1.41	-0.62	n/a	n/a	n/a
Bridges House WAA Gas	n/a	0.80	0.16	-0.58	-0.61	0.43	-2.11	-1.65	0.87
Butterwick Gas	120%	-2.02	-1.17	-0.61	-0.66	0.35	-0.17	-0.16	-0.19
Catherine Jnr School Gas	n/a	-1.42	-0.77	-1.53	-1.74	-1.68	n/a	n/a	n/a
Central Library Gas	n/a	1.25	1.43	0.97	0.86	-0.10	n/a	n/a	n/a
Charnwood AHO Main Gas	56%	-0.62	-0.59	-0.79	-1.52	0.57	-1.05	0.17	0.88
Coleman Neigh Centre Gas	156%	0.10	1.10	0.52	0.36	0.70	0.12	0.55	0.16
Coss Fam Centre Gas	n/a	-1.37	-0.71	-1.15	0.79	-2.09	n/a	n/a	n/a
Coss Pool Main Gas	65%	0.65	1.07	1.06	1.41	0.16	-1.26	0.40	0.48
Cromwell House WAA Gas	n/a	1.00	0.95	0.54	0.53	0.40	0.63	0.24	-1.30
Dudley House WAA Gas	n/a	-0.68	-0.77	-0.65	-0.78	0.22	-0.10	0.06	0.04
Elizabeth House EPH Gas	99%	0.42	0.59	0.61	0.67	0.15	1.23	1.54	-0.15
Energy Office Gas	147%	-0.96	-0.68	-1.07	-1.25	-0.37	-0.96	-0.41	-0.27
Evington Library Gas	n/a	-0.33	-0.44	-1.14	-1.23	0.70	n/a	n/a	n/a
Fred.Thorpe WAA Gas	n/a	-1.03	-0.48	-0.62	-0.66	0.22	0.13	0.29	-0.04
Gumbrill House WAA Gas	n/a	0.77	0.56	0.39	0.30	0.36	-0.10	-0.27	-0.57
Heatherbrook Sch Gas	106%	-0.37	-0.52	-1.02	-0.47	0.79	1.11	0.83	0.02
Helena Roberts WAA Gas	n/a	0.82	0.98	0.54	0.55	0.30	0.75	0.47	-1.20
Herrick Lodge EPH Gas	n/a	-1.76	-1.03	-2.63	-2.54	-3.86	n/a	n/a	n/a
Home Farm AHO Main Gas	144%	1.20	1.26	1.04	0.57	0.92	-0.89	0.72	2.49
Home Improvement Agy Gas	31%	1.58	1.39	1.37	0.98	0.64	0.02	0.64	0.16
Humberstone AHO Main Gas	194%	-0.34	-0.91	0.15	-0.50	0.79	-0.89	2.50	0.03
Jackson House WAA Gas	n/a	1.02	0.75	0.36	0.22	0.47	-0.20	-0.11	-0.10
Judgemeadow CC Gas	66%	0.38	-0.70	0.36	-0.77	-0.23	1.60	-1.05	-2.13
Lansdowne Neigh Cent Gas	29%	1.22	1.42	0.67	0.23	0.78	1.68	-0.10	-0.21
Lansdowne Pre School Gas	76%	0.48	0.50	-0.12	0.70	-0.02	-0.98	-1.22	0.12
Lough Rd Hostel Gas	n/a	1.50	1.16	0.91	0.87	0.19	-0.81	-0.46	0.57
Marlborough House Gas	11%	-0.88	-1.07	-1.37	1.52	-2.21	0.17	-1.24	-1.65
Millgate Centre Main Gas	294%	1.16	1.41	1.02	0.84	0.89	-0.34	0.55	0.31
Nether Hall School Gas	193%	0.28	-0.52	0.01	-0.60	1.38	-0.42	0.75	0.49
Netherhall Childrens Gas	49%	0.02	0.70	0.57	0.54	-1.55	0.28	-2.08	-2.06
Netherhall Neigh Cent Gas	193%	1.69	1.08	1.25	1.32	0.63	-1.02	0.01	0.05
New College Main Gas	n/a	-1.24	-0.73	-1.50	-1.14	-1.43	n/a	n/a	n/a
New Parks AHO Gas	n/a	0.13	0.56	0.51	0.15	0.56	n/a	n/a	n/a
New Parks Les Gas	205%	0.28	-0.13	-0.08	-0.46	0.74	-0.26	0.58	0.70
New Walk B Block Gas	108%	-0.68	-0.81	-1.09	-0.73	-0.98	-0.72	-0.31	0.26
New Walk Museum Gas	118%	1.74	1.50	0.98	0.96	1.05	-0.51	0.62	0.96
Norfolk House WAA Gas	n/a	-0.37	0.29	-0.05	-0.22	0.09	-0.04	0.27	0.33
Nuffield House EPH Gas	125%	0.04	0.62	1.47	1.55	0.00	-0.94	0.53	3.17
Phoenix House Gas	103%	-0.53	-0.75	0.09	0.54	-0.84	-0.52	-0.25	0.09
Pollard House WAA Gas	n/a	0.62	0.80	0.25	0.23	0.80	1.76	0.98	-1.51
Preston Lodge EPH Gas	108%	-0.02	0.87	0.26	0.28	0.12	0.66	0.97	0.11
Reference Library Gas	53%	-0.46	-0.77	-0.96	-0.87	-1.15	-0.46	-1.43	-1.47
Rowsley St AHO Gas	128%	-1.09	-0.86	-1.35	-2.15	0.44	-0.48	0.39	0.38
Rupert Hse WAA Gas	n/a	0.26	0.16	-0.37	-0.28	0.56	0.03	0.41	0.40
Saffron AHO Gas	83%	-0.61	-0.64	1.09	1.12	0.41	-0.23	0.27	-0.31
Scraptoft Valley Prim. Gas	105%	-1.06	-0.77	0.11	0.20	0.61	-1.27	-0.66	-0.30
Southfields Library Gas	230%	-0.44	-0.54	-0.27	-0.01	-1.16	-0.46	-1.13	-1.34
Spence St Hall Main Gas	n/a	-1.76	-1.58	-1.61	-1.27	-1.74	n/a	n/a	n/a
Spence St Pool Gas	52%	0.58	0.60	0.51	0.41	0.26	0.01	0.63	0.95
St Marks AHO Main Gas	n/a	1.82	1.57	1.29	0.69	0.81	n/a	n/a	n/a
St Saviours NC Gas	42%	-0.43	-0.65	-1.07	-1.40	0.62	-0.33	1.01	1.62
Sth Braunstone AHO Gas	149%	1.26	1.41	1.04	0.68	0.59	1.99	0.65	-1.37
Tatlow Rd Comm Home Gas	73%	0.13	0.93	0.65	0.73	0.23	-0.15	0.26	0.57
The City Gallery Gas	112%	-1.37	-0.85	-1.37	-1.40	-0.86	2.17	1.43	0.42
Thurnby Lodge Primary Gas	122%	-0.26	-0.58	0.29	1.40	-1.02	-0.79	-1.17	-0.13
Thurncourt EPH Gas	86%	-0.25	-1.02	0.38	0.56	-0.08	-0.07	0.55	1.06
Town Hall Gas	87%	-0.58	-0.47	-0.84	-1.01	-0.75	-0.59	-0.17	0.24
Tudor Centre Gas	48%	0.31	0.43	0.48	0.04	0.77	1.01	-0.88	-0.87
Welford House Gas	50%	-0.57	-0.79	1.04	0.56	-0.44	-0.90	-1.87	-1.51
Westcotes Library Gas	50%	-0.93	-0.72	0.45	0.27	1.25	-0.61	0.47	0.82
Whitehall Sch Main Gas	281%	0.22	0.62	0.84	0.76	0.11	0.80	0.79	-0.11

Concerning gas it was possible to calculate NPI for only 55 buildings (in a total of 81), corresponding to a success rate of 68%. Comparing the gas NPI calculated with UK benchmarks resulted in the identification of 26 buildings, corresponding to 47% of the buildings with NPI for gas consumption.

Table 39 compares gas NPI results with the standard scores results presented earlier in Table 32, Table 33, Table 34, Table 35, Table 36 and Table 37. It was possible to calculated gas load demand shape indicators and IMT parameters for 71 buildings (success rate 88%), and the application of standard scores resulted in the identification of 36 buildings, 51% of the total number of building analysed. About 12 buildings were identified both by the NPI and by at least one load demand shape indicator or IMT parameter.

From the tables above it can be easily understood that the NPI calculation is limited to the availability of floor area, and therefore the success of its calculation is lower than the calculation of load demand shape indicators and IMT parameters. This problem shows the necessity of developing benchmarks that are independent from floor area information.

NPI is a measure of absolute performance, i.e. is based on the normalisation of annual energy consumption using floor area. Conversely, the load demand shape indicators and IMT parameters are independent from floor area, the only inputs are historical records of half-hourly energy use, daily energy use and mean daily temperature, typically for one year. The indicators model specific characteristics of energy consumption, and the corresponding standard scores are a relative measure of the deviation of indicators from the average for a given building type. Therefore, NPI and the new metric would be complementary in the process of assessing building energy performance. While the NPI provides general information about energy performance, the metric provides specific information about the consumption profiles that can lead to the detection of potential energy wastage occurring systematically.

From the tables above different situations can be noticed for the relation between NPI and indicators standard scores:

- Building identified by NPI but not by the metric;
- Building not identified by NPI but identified by the metric;
- Buildings identified by both NPI and the metric.

Taking for instance the Energy Efficiency office electricity consumption, it was found that NPI is above the benchmark but the standard scores are within the band defined as ‘normal’, i.e. close to the mean values calculated for CO-type buildings. The reason for the high NPI might be the fact that this building has a reduced floor area and is densely occupied, offering different services, including a shop on the ground floor that over the period under analysis was open to the public.

The load demand profile for the Energy Efficiency office was presented in Figure 59 and compared with Attenborough house electricity demand profile in Figure 58. From this comparison it was found significant differences in terms of occupancy hours, baseload, peak demand, night-time, daytime, weekday and weekend consumption.

Attenborough house electricity consumption presents the opposite situation from the Energy Efficiency office. Attenborough house electricity NPI value is within the benchmark but indicators detected uncommon profile characteristics. In fact, it was found that Attenborough House was an untypical office building that had out-of-hours consumption due to the snooker club on the ground floor. Therefore, one can conclude that the metric was more helpful than NPI to detect bias from the expected building energy performance. Nevertheless, savings were not identified directly, the metric identified that something was uncommon in the building energy consumption profile, but not the cause of the uncommon feature. Presenting results to the energy manager can provide the information required to identify the cause of uncommon profile characteristics, and if it is possible to eliminate it and reduce energy use.

Similarly to Attenborough house, New Walk B electricity NPI was considered to be below the Carbon Trust benchmark for air-conditioned office buildings, but the metric detected high load factor, baseload, night-time consumption on weekdays and high consumption on weekends. Again, it was found that this building was not a typical office building, not only because it was fully air-conditioned, but also because it holds Leicester City Council major IT infrastructures including the main data centre. Therefore, the metric was again successful in identifying an office building with an uncommon electricity profile characteristics.

Similar occurrences were also found for buildings gas consumption. For example, the Home improvement agency gas NPI was only 31% of the set benchmark, but several indicators standard scores were significantly above one standard deviation from the mean. Observing the gas demand profile for the Home improvement agency in Figure 68 a disproportionate gas use overnight was easily detected. Again the indicators were helpful in detecting possible wastage from uncommon profile characteristics, while the NPI did not detect any problem with the building gas consumption.

For a few buildings both NPI and indicators identified excessive energy consumption and uncommon energy profile characteristics. This situation occurred for electricity use on 11 buildings and the gas consumption on 12 buildings. The metric detected in total that 26 buildings had uncommon electricity profile characteristics and 36 buildings with uncommon gas consumption characteristics.

For example St. Saviours NC was identified for high electricity use overnight, high electricity use on weekends and NPI above the benchmarks. Figure 66 presented the profiles for St. Saviours NC on weekdays and weekends, and the likely causes for this were identified has being the making and distribution of meals to the poor.

In summary, NPI and the indicators used in the new metric describe different aspects of building energy performance assessment. NPI is calculated using total energy use, and therefore offers a more general assessment of overall performance. The metric is calculated using half-hourly and daily data averaged for one year, and it is able to identify specific characteristics of the demand profiles that might indicate potential savings.

Additionally, it was found that NPI might be difficult to calculate because it requires floor area data, which is not always available or is accurately measured. The comparison of NPI to the Carbon Trust benchmark resulted in the identification of about half of the buildings for excessive energy consumption (56% for electricity and 47% for gas consumption). This is a very high number of buildings identified as having poor electricity and gas performance. This could be originating by outdated NPI benchmarks, but it is not possible to confirm this as a fact.

Concerning load demand shape indicators and IMT parameters it was found that they are more specific to point out the causes of deviations from expected profiles. The metric detects profile deviations, in terms of specific features that may be indicative of potential energy wastage: high load factor, high baseload, overnight and weekend consumption. Nevertheless, it was not possible to identify the actual causes of the deviations from the expected profile. For that it would be necessary to acquire more information, by talking with the energy manager or building manager, and/or visiting the site and talking to the building occupants. Interacting with the building manager and building occupants is a common practice in most of the manual diagnostics techniques. The on-site investigation, presentation and discussion of findings with the energy manager is fundamental to diagnose the causes of potential faults, as described in Whole Building Diagnostics (Claridge, et al., 1999) and Operation Diagnostics presented in (Visier, 2005).

From the current work it was found that the causes for deviation from expected profile could not be related to energy efficiency measures, such as the existence of the snooker club in Attenborough house. However, in most buildings analysed it was found, and confirmed with Leicester energy management team, that indicators pointed out the existence of opportunities to reduce energy and carbon emissions from reducing consumption on non-occupied periods (overnight, on weekends, etc.), non-weather related gas use, dependency of outside temperature and reducing internal temperature set points. These may be seen as 'low hanging fruits' but these types of measures have saved Leicester City Council more than 225,000 Euro per year (2006 figures) (Ferreira, et al., 2007). The recent pilot study conducted by the Carbon Trust on the use of aM&T in SME concluded that these systems identified 12% of carbon savings, and an average of 5% carbon savings were implemented through reduced energy consumption. These results were attained using conventional software packages equipped with simple visualisation techniques and primary meter electricity and gas half-hourly data. The introduction of the metric developed under the current work could improve the cost-effectiveness of the aM&T systems, by increasing the automation of the process and providing information on which energy managers can support the implementation of energy saving measures.

10.3. Further research

The metric developed under the current work is to be considered a first step for automating the analysis and interpretation of primary energy meter short time series data. Further research is needed to improve the proposed metric, but this will require a larger database of half-hourly electricity and gas consumption for a wide range of building types. Primary meter half-hourly electricity and gas data from non-domestic buildings, but also for businesses and the residential sector, can be used to produce UK benchmarks, similar to the NPI for annual consumption benchmarks published by the Carbon Trust. Nonetheless, there are still some improvements that can be introduced to improve the inference of the metric.

The metric can probably be improved to provide a fully automated analysis of building primary metered electricity and gas half-hourly data. The results from the application of the metric could be more informative if additional data about the buildings was available.

For example, if information about building services was available this could be used to introduce more detailed building types, and produce more precise benchmarks. A practical way of doing would be to use the full potential of the Pclass codes. Bruhns, et al. (2000) defined 2000 sub-divisions for Pclass. For instance in this study we use a general classification of office buildings using CO Pclass. However the Pclass codes can be use to classify administrative and office buildings in several categories, for example: CO10 for commercial offices, CO101 for studio offices, CO111 for bank or building society office, CO114 for legal and financial services office, CO121 for warehouse office, CO122 for factory office and CO_2 for local government offices. Note that for producing robust benchmarks for the UK using for load demand profiles and IMT parameters it would require a large dataset of half-hourly electricity and gas consumption and mean daily temperature for the different locations.

A national benchmark could be extended to include other buildings' utilities that are being measured in short time series periods, for example water and heat. A national benchmark should also include parameters for air-conditioned buildings, i.e. application of the IMT model to building half-hourly electricity consumption. The application of IMT model to electricity consumption was found to produce a weak correlation with temperature in most Leicester City Council buildings. This was mainly due to the fact that few Leicester buildings are air-conditioned. However, it should be possible to compute IMT parameters from electricity consumption of air-conditioned buildings.

The IMT model can be adapted to the introduction of other independent variables (Kissock, et al., 2003). Further research can focus on assessing the influence of more than one independent variable on building energy consumption, for example outside temperature and solar radiation.

Concerning the calculation of load demand shape indicators, a minor adjustment could be introduced. Instead of using fixed occupancy hours for all the buildings, the indicators' meaningfulness could be improved by using real occupancy and operating hours. The calculation of load demand shape indicators included dividing the daily demand profile in night (from 22h00 to 6h00), office working hours (from 8h00 to 18h00) and lunch period (from 12h00 to 14h00). However, it is only possible to use the real operating hours, if this information is readily available. This would allow the use of additional load demand shape indicators. For instance, the load factor for office hours α_{D3}, the modulation coefficient $\alpha_{D4,}$ the baseload uniformity factor α_{D6} and the lunchtime impact α_{D9}, which were found not to be suitable for the analysis mainly because there was a mismatch between real occupancy and selected periods.

Additional research is required on the use of the metric for 'real-time' event detection. M&T has been using energy performance lines and CUSUM to identify changes in consumption pattern, as presented by Harris (1989). Typically CUSUM is used for conducting M&T based on historical records of data. Brown and Wright (2007) found that wavelet transforms could also be used for event detection, and that there was correlation for event detection between the wavelet and CUSUM.

Generally, all the automated tools for continuous diagnostics include some kind of event detection methodology for triggering alarms, (Friedman & Piette, 2001) The event detection procedures can be based on simple high or low thresholds and user-defined rules. There are also more sophisticated approaches such as the use of statistical process control techniques, Fourier series, artificial neural networks and Fuzzy logic models suggested in (Abushakra, 1999; Piette, 1999; Haves, 1999). Yang, et al. (2005) offers a review of some artificial neural network models to 'real-time' prediction of building energy consumption.

The metric developed and presented in the current work could be used together with the advanced event detection techniques to investigate the possibility of automatically detecting of bias in profiles building electricity and gas consumption, which for load demand shape indicators could be done in 'real time', i.e. in half-hourly intervals. This would only be possible if the meter technology used allowed continuous data communication, which is not the case in Leicester City Council system. However, most of the smart metering technology that uses the Internet to transmit energy consumption is able to do it 'real time' over the Internet, and even register consumption in shorter periods than the half-hour.

Chapter 11. Conclusions

The aim of this research project was to assess the usefulness of primary energy meter short time series data to identify energy saving opportunities in non-domestic buildings. An extended literature review on data analysis, including a questionnaire survey to understand the current practices and needs of European municipal energy managers was completed. Half-hourly electricity and gas consumption and outside temperature data were applied to a metric that characterised the demand profiles of 81 municipal buildings in Leicester. The metric composed of 8 indicators was used to conduct a benchmarking exercise for each building type, which allowed the identification of uncommon profile characteristics that may be indicative of energy saving opportunities from undetected wastage.

This research achieved its objectives to the extent that it was possible to develop and validate a methodology for the analysis and interpretation of primary meter short time series electricity and gas consumption from municipal buildings. This new approach improves current practice by eliminating the subjectivity of visual interpretation of plots. The novel metric characterised building energy performance according to different indicators. These indicators were related to uncommon profile characteristics that can lead to the identification of energy wastage. The comparison of indicators for buildings of the same type, using standard scores, supported a new benchmarking framework that enabled the identification of specific buildings that had uncommon load demand profile characteristics and/or gas dependency on outside temperature.

11.1. Research outcomes

Primary meter short time series building electricity and gas consumption data is becoming increasingly available from aM&T, BEMS and smart metering systems. Current practice is based on the use of NPI and benchmarking, M&T techniques for monthly data and other visual tools to manually analyse short time series data. The current practice discussed in previous chapters contains several shortcomings. The use of NPI is limited to the availability of floor area information, which is not so readily available as expected even with the recent regulations for the compulsory display of building energy certificates – DEC. M&T techniques are included in several software packages, but these are simple visualisation and process control techniques suitable to monitor and target monthly energy consumption. M&T is not easily adapted to assess building performance and to identify savings using short time series data.

More advanced visualisation tools were found to be helpful in analysing half-hourly electricity and gas consumption data, and to conduct manual diagnosis to improve building operation. However, their effectiveness is linked with the experience of the energy analyst. Alternatively, automated diagnostics tools are independent of the analyst experience. Nevertheless existing automated diagnostics tools are not suited for single metered energy consumption data. Automated diagnostics are being developed for analysing the abundant data generated by BEMS systems, and not smart metering data that is mostly primary meter total energy use in short-time series.

This research introduced a systematic approach for the diagnostics of building operation using primary meter half-hourly electricity and gas consumption data, and daily mean outside temperature data. The approach, based on a metric composed by load demand shape indicators and IMT parameters, is able to characterise quantitatively different aspects of building energy performance. Indicators modelled the shape of the average load demand electricity and gas profiles. Buildings' thermal performance and correlation with outside temperature was modelled using IMT parameters.

The load shape profile indicators applied to gas and electricity analysis were able to characterise energy use at different times of the day. The IMT parameters from energy performance lines were useful to analyse gas consumption data - which was correlated with outside temperature for most of the buildings. Buildings with untypical electricity and gas consumption characteristics were identified through a comparative study - benchmarking - using standardised scores.

This benchmarking study compared buildings of similar type, and identified those that differ significantly from 'typical'. 'Significantly' was defined as more than one standard deviation from the mean. Therefore, this benchmarking analysis allowed the identification of buildings that by their intrinsic or/and operational characteristics differ from similar buildings. Most of the uncommon demand profile features identified were confirmed on the discussion of results with Leicester City Council energy management team. Not all features were related to energy efficiency measures. Nevertheless, the proposed approach, offered, for the first time, a systematic and semi-automated procedure to identify potential faults using short-time series primary meter data. One can refer to tgis approach as semi-automated because all the process, from the calculation of indicators to the benchmarking, can be conducted automatically using the database and software with the algorithms proposed in the current work. However, the confirmation of energy efficiency measures has to be done manually, through a site or a discussion with the energy manager, or building caretaker. The potential faults in buildings, or 'failure modes', which have been considered in this research, were:

- Fixed, non-weather related energy use;
- Dependency of energy use and temperature during the heating season;
- Base temperature, below which heating system are turned-on;
- Intensity of energy use;
- Baseload consumption;
- Energy use when building unoccupied on night-time on weekdays;
- Energy use when building unoccupied on night-time on weekends;
- Energy use when building unoccupied on weekends.

11.2. Intended contribution of the research

This thesis contributes to improve the objectivity of building primary meter half-hourly electricity and gas consumption data analysis. The interpretation of building consumption data in short time series periods can now be streamlined, automated and incorporated in existing aM&T software tools.

This thesis comprised a large empirical study of the analysis of short time series energy data, and is probably the first to include the analysis of half-hourly gas consumption. The literature review found very few references to large-scale empirical studies with a significant number of buildings. Claridge et al. (1999) mentions that their manual diagnostics approach was tested in more than 100 buildings, but no evidence is shown on the data analysed. Similarly, the evaluation of Texas Loan Star programme presented by Haberl, et al. (1998) estimates the savings accomplished by the Government energy efficiency subsidies for retrofitting in 298 buildings where metering was installed. Note that the latter refers mostly to the analysis of electricity data (from primary meter and sub-meter). Another empirical study on the use of aM&T short time series data was conducted not on buildings but on 582 SME across the UK. The Carbon Trust carried out this study and results are available on (Carbon Trust, 2007b). However, no evidence was available on the data analysis and results on site-by-site basis. The increasing availability of smart metering will surely increase the number and quality of empirical studies using short time series building energy consumption data.

The current work was based on the state of the art of techniques used for the analysis of time series energy consumption data. It was found that generally there are 3 different approaches to building energy management using real time series data: benchmarking using annual data, M&T using monthly (and possibly weekly) data and manual and automated diagnostics using hourly or sub-hourly data. The latter is an area of intense research, particularly on the use of BEMS data to detect and diagnose faults in order to improve building energy performance. The work challenged the current knowledge on manual and automated diagnostics techniques applied to BEMS systems by investigating a methodology that can be used to perform automated diagnostics in buildings, but using only primary energy meter consumption data, outside temperature and classification of building type. The current work confirmed the potential for the use of smart metering data to conduct building energy performance assessment and to identify potential opportunities for reducing energy use and carbon emission in non-domestic buildings. Nevertheless, the identification of savings by the novel benchmarking approach needs to be confirmed by a site visit that includes a discussion with the building manager.

The contribution to knowledge of the current work is a methodology that characterises and assesses building electricity and gas consumption profiles. This benchmarking technique works with limited data inputs: building primary meter short time series electricity and gas consumption data, outside temperature data and information about building type. This information is already readily available for some building managers, and its availability is expected to increase in the coming years, with the deployment of smart metering driven by existing and new legislation. The methodology can be automated in the future and its validity increased by adding more buildings and datasets to the database. The more buildings are added the more meaningful are the standards and the benchmarking.

This research contributes positively to the development of the building energy management discipline, and provides energy managers and energy users with a new tool to reduce consumption and consequently carbon emissions in buildings.

11.3. Future applications of the research

It can be argued that this innovative benchmarking framework using short time series data requires more buildings in order to represent UK municipal building stock, or the UK non-domestic building stock. And in fact this is true. However, this research is to be taken as a first step in the development of new benchmarks for the analysis of primary meter short time series electricity and gas consumption. As more buildings are added to the database the more robust the benchmarks will become, in what can be seen as a self-regulating and self-updating process.

This research can also be understood as the development of a benchmarking framework to be used on multi-site organisations. The current work focused on local authority buildings, but the application of the metric could be quite powerful if applied to an organisation with similar installations distributed across different locations, such as for example a supermarket chain, banks, etc. It would be expected that different sites would have very similar consumption patterns. The metric could then be used to produce very reliable benchmarks for the different characteristics of the profiles and support the automatic identification of changes in consumption patterns of the similar buildings in different locations.

Another possibility is to apply the benchmarking on a large scale, and use utility short time series databases used for billing to provide tailored energy efficiency advice to energy users. Policy recommendations in the UK and in Europe are pushing the promotion of smart metering and more informative billing in order to promote energy efficiency. This metric can for example be applied to large utilities' databases that hold energy consumption in short time series, and automatically produce tailor made advice for the different customers. From the application of this metric it would be possible, for example, to suggest to users that they are using more energy at night than the average. This advice could be given in the utility bill, together with additional advice on possible causes of excessive energy use. In summary, the use of energy metered data and the new benchmarking framework would produce relevant information that could be used to decrease electricity and gas demand in buildings.

Publications arising from this thesis

During the research programme several peer-reviewed academic papers were submitted and approved for publication:

Ferreira, V. and Fleming, P. (2009) Evaluation of water and energy metering and monitoring practices in European local authorities. ECEEE Summer Study 2009. Cote D'azur.

Ferreira, V., Alves, L., Basanez-Unanue, G., Gonzalez, M., Tourlis, N. Pasinetti, R., Siciliano, A. and Kenny, P. (2008) Lessons learned from the implementation of metering and monitoring systems in public buildings in Europe – ENERinTOWN project, In: proceedings of Improving Energy Efficiency in Commercial Building Conference. Frankfurt.

Ferreira, V., Alves, L., Fleming, P., Stuart, G., Patel, P., Webber, P. and Conway, S. (2007) "Low hanging fruits" or cost-effective energy and water savings using intelligent metering and monitoring systems?, In proceedings of 2007 ECEEE Summer Study. Cote D'Azur.

Ferreira, V., Fleming, P., and Stuart, G. (2006). Intelligent energy and water performance assessment in municipal buildings. In: proceedings of the Fourth Conference on Improving Energy Efficiency in Commercial Building Conference. IEECB'06 Frankfurt.

Additionally, the author submitted a summary of the thesis to the EDP Richard Branson innovation award, and was selected between for the 2nd stage of the evaluation process, in: http://aeiou.visao.pt/premio-inovacao-selecciona-16-projectos=f506415 [Accessed on 16th May 2009]

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Appendix A – Questionnaire Survey of Energy and Water Metering and Monitoring practices in European Municipal buildings

List of respondents

1. Geislingen
2. City of York Council
3. Durham County Council
4. Wirral MBC
5. Stadt Saarbrücken
6. West Sussex County Council
7. Spelthorne BC
8. Sefton Council
9. North Yorkshire County Council
10. Leicester City Council
11. City Council Bielsko-Biala
12. Derby City
13. Municipalty of Tilburg
14. Comune di Salerno
15. City of Heidelberg
16. Doncaster Council
17. Braintree District Council
18. EVE - Pais Vasco
19. Comune di Albignasego
20. Municipality of Almada
21. Milton Keynes Council
22. Viernheim
23. Bury Metro Borough Council
24. Galway City Council
25. Town of Krnov
26. London Borough of Islington
27. Calderdale MBC
28. Kirklees Metropolitan Council

29. Lausanne
30. Mairie de Montmélian
31. Hull City Council
32. Conseil régional de Franche Comté
33. Sofia Municipality
34. Chesterfield Bororugh Council
35. City of Helsinki
36. Frankfurt a.M.
37. Vila Nova de Gaia
38. Skaftarhreppur
39. Haljala Municipality
40. Amstetten
41. Moravske Toplice
42. City of Stuttgart
43. Cork County Council
44. Vale of Glamorgan Council
45. Kohtla-Järve Town Coverment
46. The City of Reykjavik
47. Hampshire County Council
48. Magistrat Linz
49. Municipality Dobrichka
50. Eslövs Kommun
51. Umeå Kommun
52. Delémont
53. Municipality of Velenje
54. Association of Polish Local Authorities
55. North Ayrshire Council
56. Jõhvi
57. Municipality of Georgioupolis
58. Pertrh & Kinross Council
59. Glasgow City Council
60. South Lanarkshire Council
61. South Staffordshire
62. Scottish Borders Council

63. Comune di Rimini
64. Town of Harrjavalta
65. Dublin City Council
66. Kuressaare city
67. East Sussex County Council
68. Tallinn City Government
69. Durham County
70. ENER'GENCE
71. comune di Rimini
72. Aberdeen City Council
73. City of Utrecht
74. Lewes District Council
75. Syndicat Intercommunal des Energies de la Loire
76. Ville de Neuchâtel

Survey introduction letter

Dear Municipal Energy Manager,

Here at the Institute of Energy and Sustainable Development we need your help.

A research project under the supervision of Prof. Paul Fleming is investigating water and energy metering and monitoring practices in European Municipal buildings.

This survey is being conducted under a PhD research programme of the Institute of Energy and Sustainable Development – De Montfort University, in the UK , in cooperation with the Instituto Superior Técnico in Portugal .

A survey questionnaire has been devised in order to collect information on current practices and future requirements for one of the most important tools for municipal management - metering and monitoring of water and energy consumption in buildings.

The municipal buildings which are to be considered in this survey are typically non-domestic buildings: town halls, office buildings, leisure centres, museums, libraries, depots, sports halls, swimming pools, community centres, day centres and school buildings.

We would appreciate very much if you could take a few minutes to complete this questionnaire. The information entered into our database will be made confidential, and no references to your name or to your local authority will be made in any publishable work without your previous consent.

We hope you will want to collaborate in this investigation, and we shall send you a summary of the results as soon as they are available.

Thank you very much for your cooperation.

Yours sincerely,

Vasco Guedes Ferreira

For additional information, please contact:

Vasco Guedes Ferreira

Tel.: +351 21 841 94 06

Skype: vascogf

E-mail: vferreira@ist.utl.pt

Questionnaire on water and energy metering and monitoring practices in European municipal buildings

Local authority name:

Number of municipal buildings:

Country:

Contact name:

E-mail:

Phone number:

1. Does your local authority collect water and energy (electricity, gas, heat, etc) consumption data from municipal buildings?

Please, tick Yes or No for each of the following items.

Water		
Electricity		
Gas		
Heat		
Oil		
Biomass		
Solar thermal		
Coal		
Outside temperature		
Internal temperature		
Other, please add details		

2. How is data on water and energy consumption in municipal buildings collected in your local authority?

Please, tick all that apply.

	Manual meter readings	Utility paper bills	Utility electronic bills	Automatic metering system
Water	☐	☐	☐	☐
Electricity	☐	☐	☐	☐
Gas	☐	☐	☐	☐
Heat	☐	☐	☐	☐
Oil	☐	☐	☐	☐
Biomass	☐	☐	☐	☐
Solar thermal	☐	☐	☐	☐
Coal	☐	☐	☐	☐
Outside temperature	☐	☐	☐	☐
Internal temperature	☐	☐	☐	☐
Other	☐	☐	☐	☐

3. What is the metering frequency of water and energy consumption metering?

Please, tick all that apply.

	Half-hourly or less	Daily	Weekly	Monthly	Bi-monthly	Quarterly	Annually	Intermit-tently
Water	☐	☐	☐	☐	☐	☐	☐	☐
Electricity	☐	☐	☐	☐	☐	☐	☐	☐
Gas	☐	☐	☐	☐	☐	☐	☐	☐
Heat	☐	☐	☐	☐	☐	☐	☐	☐
Oil	☐	☐	☐	☐	☐	☐	☐	☐
Biomass	☐	☐	☐	☐	☐	☐	☐	☐

Solar thermal	☐	☐	☐	☐	☐	☐	☐	☐
Coal	☐	☐	☐	☐	☐	☐	☐	☐
Outside temperature	☐	☐	☐	☐	☐	☐	☐	☐
Internal temperature	☐	☐	☐	☐	☐	☐	☐	☐
Please add comments								

4. What departments have the responsibility for collecting municipal buildings water and energy data?

Please, tick all that apply.

	Municipal Financial Department	Municipal Property Department	Municipal Environmental Department	Municipal Energy Agency	Multi-local authority structure	Private consultant on sub-contract
Water	☐	☐	☐	☐	☐	☐
Electricity	☐	☐	☐	☐	☐	☐
Gas	☐	☐	☐	☐	☐	☐
Heat	☐	☐	☐	☐	☐	☐
Oil	☐	☐	☐	☐	☐	☐
Biomass	☐	☐	☐	☐	☐	☐
Solar thermal	☐	☐	☐	☐	☐	☐
Coal	☐	☐	☐	☐	☐	☐
Outside temperature	☐	☐	☐	☐	☐	☐
Internal temperature	☐	☐	☐	☐	☐	☐
Please add comments						

5. Do you have a computer database to store the water and/or energy consumption data of your municipal buildings?

Please, tick Yes or No for each of items stored on the computer database.

	Yes	No
Water	○	◉
Electricity	○	◉
Gas	○	◉
Heat	○	◉
Oil	○	◉

Biomass		
Solar thermal		
Coal		
Outside temperature		
Internal temperature		
Other, please add details		

6. What is the water and/or energy data used for?

Please, tick all that apply.

To verify utility billing data	
To negotiate with utilities (e.g. in calls for tender for energy supply)	
To ensure that consumption is within the utility contract and avoid penalties	
To identify excessively high levels of consumption in normal use	
To monitor unusually high or low consumption to identify energy wastage	
To check for faults affecting consumption permanently	
To perform benchmarking analysis with similar buildings	
To measure municipal buildings greenhouse gas emissions	
To prepare dossiers for performance contracting in municipal property	
To measure and verify energy/water savings measures	
To communicate with buildings occupants in order to change behaviour	
To communicate with general public, by displaying building performance	
Not effectively used	
Other, please specify:	

7. What are the techniques do you use to analyse water and/or energy consumption data?

Please, describe the methodology and the techniques used for visualising and analysing data.

8. Do you use any of the following techniques to analyse water and/or energy consumption data?

Please, tick all that apply.

Normalised Performance Indicator (for example: m^3 of water/ m^2, kWh/m^2, tonnes CO_2 emitted)	☐
Current and Past Consumption (for example: comparison of consumption in March 2005 against March 2006)	☐
Simple trend line (for example: energy against time)	☐
Refined trend line (for example: energy and water against time with moving averages)	☐
Regression analysis (for example: energy against outside temperature)	☐
Profiles (for example: weekly and daily consumption patterns)	☐

9. Is there a standard rating system or benchmarks for the water and/or energy performance assessment in municipal buildings in your country? Please, tick Yes or No.

Yes	No
	◉

10. Does your local authority have an analysis software system for municipal building water and/or energy data? Please, tick Yes or No.

Yes	No
	◉

If Yes, please answer the following questions;
If No, please go directly to the last question.

11. What are the input variables for the analysis software system?

Please tick all that apply.

	Yes	No
Water	○	◉
Electricity	○	◉
Gas	○	◉
Heat	○	◉

Oil	○	◉
Biomass	○	◉
Solar thermal	○	◉
Coal	○	◉
Outside temperature	○	◉
Internal temperature	○	◉
Other, please add details		

12. What is the name of water and/or energy analysis software in use in your local authority?

13. Does the software system identify automatically possible action to be taken to improve energy efficiency in your local authority municipal buildings? Please, tick Yes or No.

Yes	No
	◉

14. Please, describe the features and/or analysis techniques do you need and expect to be included in a municipal building water and energy metering and monitoring system?

Appendix B – Matlab© programming code

The following table presents a summary of MATLAB code structure developed under this research, including full the algorithms code.

Functionality	Files Involved	Notes
Connect to the Database	Connect_MSSQL.m	-
Saving data – CSV Files	File_Save3DCSV.m File_SaveDailyTotalsCSV.m File_SaveIndicatorsCSV.m File_SaveNonWeatherCSV.m File_SaveWeatherCSV.m	Save the data on screen in a CSV format... The name will identity what ...
Saving data - Image files	File_SaveNonWeatherFigure.m File_SaveWeatherFigure.m File_Save3DFigure.m File_SaveDailyTotalsFigure.m	Saves the graph on screen in an image format... The name of file will identify which graph saving...
View Indicators	HandleControls_ViewIndicators.m MS_Get_Indicators_V3.m	-
Calculate Weather Indicators (4-parameter IMT model)	HandleControls_CalculateIndicators.m HandleControls_CalculateWeatherIndic ators.m MS_Save_WeatherIndicators.m	Calculates and saves the weather indicators on the database
Calculate Non-Weather Indicators (load demand shape indicators)	HandleControls_CalculateIndicators.m MS_Calculate_NonWeatherIndicators.m	Calculates and saves the non-weather indicators on the database
View Non-Weather Graphs	HandleControls_InitiateViewNonWeathe r.m MS_Get_AverageDailyPlot.m	-
View Weather Graphs	HandleControls_InitiateViewWeather.m MS_Get_EnergyVSTemperaturePlot.m HandleControls_CalculateWeatherIndic ators.m	the last file is repeated (from the 'Calculate weather Indicators') because it calculates the Best Fit option, which is the same done when calculating the weather indicators...
View 3D Graph	HandleControls_InitiateView3D.m MS_Get_SurfaceChart_V2.m	-
View Daily Totals	HandleControls_InitiateViewDailyTotals. m MS_Get_DailyTotals_Daily.m MS_Get_DailyTotals_Monthly.m MS_Get_DailyTotals_Weekly.m	-

Connect_MSSQL.m

```
function [con] = Connect_MSSQL()

con = database('sql', 'sa', 'sapassword');
```

File_Save3DCSV.m

```
function [no] = File_Save3DCSV()

global DataToPlot

[filename, pathname] = uiputfile({'*.*','All Files';'*.csv','Comma-Separated Value (*.csv)'},'Please select the name of the target file...');

%%M = [cell2mat(DataToPlot(:,1)), cell2mat(DataToPlot(:,2))];

%M = [cell2mat(DataToPlot(:,1)), cell2mat(DataToPlot(:,2)), cell2mat(DataToPlot(:,3)), cell2mat(DataToPlot(:,4)), cell2mat(DataToPlot(:,5)), cell2mat(DataToPlot(:,6)), cell2mat(DataToPlot(:,7)), cell2mat(DataToPlot(:,8)), cell2mat(DataToPlot(:,9)), cell2mat(DataToPlot(:,10))];

%DataToPlot %= {'123' , '123123123', ''}

%dlmwrite([pathname filename],DataToPlot,',')

fid = fopen([pathname filename],'W');

Ncolumns= size(DataToPlot, 2);

Nlines= size(DataToPlot, 1);

fwrite(fid,['Year, Month, Day, TimeAsNumber, Movement']);

for i=1:Nlines

   for j=1:Ncolumns

      fwrite(fid,[num2str(DataToPlot{i,j}) ',']);

   end

   fwrite(fid,char(10));

end

fclose(fid);
```

File_SaveDailyTotalsCSV.m

```
function [no] = File_SaveDailyTotalsCSV()

global DataToPlot

[filename, pathname] = uiputfile({'*.*','All Files';'*.csv','Comma-Separated Value (*.csv)'},'Please select the name of the target file...');
```

```
%%M = [cell2mat(DataToPlot(:,1)), cell2mat(DataToPlot(:,2))];
%M = [cell2mat(DataToPlot(:,1)), cell2mat(DataToPlot(:,2)), cell2mat(DataToPlot(:,3)), cell2mat(DataToPlot(:,4)), cell2mat(DataToPlot(:,5)), cell2mat(DataToPlot(:,6)), cell2mat(DataToPlot(:,7)), cell2mat(DataToPlot(:,8)), cell2mat(DataToPlot(:,9)), cell2mat(DataToPlot(:,10))];
%DataToPlot %= {'123' , '123123123', ''}
%dlmwrite([pathname filename],DataToPlot,',')
fid = fopen([pathname filename],'W');
Ncolumns= size(DataToPlot, 2);
Nlines= size(DataToPlot, 1);
for i=1:Nlines
   for j=1:Ncolumns
      fwrite(fid,[num2str(DataToPlot{i,j}) ',']);
   end
   fwrite(fid,char(10));
end
fclose(fid);
```

File_SaveIndicatorsCSV.m

```
function [no] = File_SaveIndicatorsCSV()
global DataToPlot
[filename, pathname] = uiputfile({'*.*','All Files';'*.csv','Comma-Separated Value (*.csv)'},'Please select the name of the target file...');
%%M = [cell2mat(DataToPlot(:,1)), cell2mat(DataToPlot(:,2))];
%M = [cell2mat(DataToPlot(:,1)), cell2mat(DataToPlot(:,2)), cell2mat(DataToPlot(:,3)), cell2mat(DataToPlot(:,4)), cell2mat(DataToPlot(:,5)), cell2mat(DataToPlot(:,6)), cell2mat(DataToPlot(:,7)), cell2mat(DataToPlot(:,8)), cell2mat(DataToPlot(:,9)), cell2mat(DataToPlot(:,10))];
```

```
%DataToPlot %= {'123' , '123123123', ''}

%dlmwrite([pathname filename],DataToPlot,',')

fid = fopen([pathname filename],'W');

Ncolumns= size(DataToPlot, 2);

Nlines= size(DataToPlot, 1);

for i=1:Nlines

    for j=1:Ncolumns

        fwrite(fid,[DataToPlot{i,j} ',']);

    end

    fwrite(fid,char(10));

end

fclose(fid);
```

File_SaveNonWeatherCSV.m

```
function [no] = File_SaveNonWeatherCSV()

global DataToPlot

[filename, pathname] = uiputfile({'*.*','All Files';'*.csv','Comma-Separated Value (*.csv)'},'Please select the name of the target file...');

%%M = [cell2mat(DataToPlot(:,1)), cell2mat(DataToPlot(:,2))];

M = [cell2mat(DataToPlot(:,1)), cell2mat(DataToPlot(:,2)), cell2mat(DataToPlot(:,3)), cell2mat(DataToPlot(:,4)), cell2mat(DataToPlot(:,5)), cell2mat(DataToPlot(:,6)), cell2mat(DataToPlot(:,7)), cell2mat(DataToPlot(:,8)), cell2mat(DataToPlot(:,9)), cell2mat(DataToPlot(:,10))];

csvwrite([pathname filename],M)
```

File_SaveWeatherCSV.m

```
function [no] = File_SaveWeatherCSV()

global DataToPlot

[filename, pathname] = uiputfile({'*.*','All Files';'*.csv','Comma-Separated Value (*.csv)'},'Please select the name of the target file...');

%%M = [cell2mat(DataToPlot(:,1)), cell2mat(DataToPlot(:,2))];

M = [cell2mat(DataToPlot(:,1)), cell2mat(DataToPlot(:,2))];

csvwrite([pathname filename],M)
```

File_SaveNonWeatherFigure.m

```
function [no] = File_SaveNonWeatherFigure(handles)

global DataToPlot

% Get the file name to save...

[filename, pathname] = uiputfile({'*.jpg','JPEG image';'*.fig','Matlab Figure';'*.*','All Files'},'Please select the name of the target file...');

% create a new figure for saving and printing...

fig2 = figure('visible','on');

% copy axes into the new figure...

newax = copyobj(handles.graph_NonWeather,fig2);

% Arange the graph to take all figure...

set(newax, 'units', 'normalized', 'position', [0.13 0.11 0.775 0.815]);

% Save the figure...

saveas(newax, [pathname filename]);

% Close the figure

close(fig2);
```

File_SaveWeatherFigure.m

```
function [no] = File_SaveWeatherFigure(handles)

global DataToPlot

% Get the file name to save...

[filename, pathname] = uiputfile({'*.jpg','JPEG image';'*.fig','Matlab Figure';'*.*','All Files'},'Please select the name of the target file...');

% create a new figure for saving and printing...

fig2 = figure('visible','on');

% copy axes into the new figure...

newax = copyobj(handles.graph_Weather,fig2);

% Arange the graph to take all figure...

set(newax, 'units', 'normalized', 'position', [0.13 0.11 0.775 0.815]);

% Save the figure...

saveas(newax, [pathname filename]);

% Close the figure

close(fig2);
```

File_Save3DFigure.m

```
function [no] = File_Save3DFigure(handles)

global DataToPlot

% Get the file name to save...

[filename, pathname] = uiputfile({'*.jpg','JPEG image';'*.fig','Matlab Figure';'*.*','All Files'},'Please select the name of the target file...');

% create a new figure for saving and printing...

fig2 = figure('visible','on');

% copy axes into the new figure...

newax = copyobj(handles.graph_3D,fig2);
```

```
% Arange the graph to take all figure...

set(newax, 'units', 'normalized', 'position', [0.13 0.11 0.775 0.815]);

colorbar();

% Save the figure...

saveas(newax, [pathname filename]);

% Close the figure

close(fig2);
```

File_SaveDailyTotalsFigure.m

```
function [no] = File_SaveDailyTotalsFigure(handles)

global DataToPlot

% Get the file name to save...

[filename, pathname] = uiputfile({'*.jpg','JPEG image';'*.fig','Matlab Figure';'*.*','All Files'},'Please select the name of the target file...');

% create a new figure for saving and printing...

fig2 = figure('visible','on');

% copy axes into the new figure...

newax = copyobj(handles.graph_DailyTotals,fig2);

% Arange the graph to take all figure...

set(newax, 'units', 'normalized', 'position', [0.13 0.11 0.775 0.815]);

% Save the figure...

saveas(newax, [pathname filename]);

% Close the figure

close(fig2);
```

HandleControls_ViewIndicators.m

```
function [no]= HandleControls_ViewIndicators(handles)

global SelectedProjectID handle_table DataToPlot tablenotbuilt

%cell_data = {'qwee qwe qweqweqwe' 'qwee qwe qweqweqwe' 'qwee qwe qweqweqwe' 'qwee qwe qweqweqwe' 'qwee qwe qweqweqwe' 'qwee qwe qweqweqwe' 'qwee qwe qweqweqwe' 'qwee qwe qweqweqwe' 'qwee qwe qweqweqwe' 'qwee qwe qweqweqwe' 'qwee qwe qweqweqwe' 'qwee qwe qweqweqwe' 'qwee qwe qweqweqwe' 'qwee qwe qweqweqwe' };

titles={    ...

        'Building Name','Channel Description','Daily 1','Daily 2','Daily 3','Daily 4','Daily 5','Daily 6','Daily 7','Daily 8','Daily 9' ...

        ,'Weekly 1','Weekly 2','Weekly 3'...

        , 'Weekday C', 'Weekday B1', 'Weekday B2', 'Weekday B3', 'Weekday RMSE 1', 'Weekday RMSE 2', 'Weekday R^2 1', 'Weekday R^2 2' ...

        , 'Weekdays TTest-pval-C 1', 'Weekdays TTest-pval-C 2', 'Weekdays TTest-pval-m 1', 'Weekdays TTest-pval-m 2' ...

        , 'Weekdays TTest-t-C 1' , 'Weekdays TTest-t-C 2', 'Weekdays_TTest-t-m 1', 'Weekdays_TTest-t-m 2' ...

        , 'Weekdays FTest-pval 1', 'Weekdays FTest-pval 2', 'Weekdays FTest-f 1', 'Weekdays FTest-f 2' ...

        , 'Weekdays MSE 1', 'Weekdays MSE 2' ...

        , 'Weekend C', 'Weekend B1', 'Weekend B2', 'Weekend B3', 'Weekend RMSE 1', 'Weekend RMSE 2', 'Weekend R^2 1', 'Weekend R^2 2' ...

        , 'Weekend TTest-pval-C 1', 'Weekend TTest-pval-C 2', 'Weekend TTest-pval-m 1', 'Weekend TTest-pval-m 2' ...

        , 'Weekend TTest-t-C 1' , 'Weekend TTest-t-C 2', 'Weekend_TTest-t-m 1', 'Weekend_TTest-t-m 2' ...

        , 'Weekend FTest-pval 1', 'Weekend FTest-pval 2', 'Weekend FTest-f 1', 'Weekend FTest-f 2' ...

        , 'Weekend MSE 1', 'Weekend MSE 2' ...
```

```
            , 'PClass', 'LCC_floor_area' ...
        };
cell_data= MS_Get_Indicators_V3(num2str(SelectedProjectID));
if strcmp(cell_data{1},'No Data')~=1
else
    cell_data=cell(1,length(titles))
    errordlg('No Data was found!', 'System message...')


end
if handle_table.Visible==0 || tablenotbuilt
    handle_table= uitable(handles.figure_TES, cell_data,titles);
    handle_table.position= [480, 110, 550, 420];
    handle_table.Visible= 1;
    tablenotbuilt= false;
end
DataToPlot= [titles;cell_data];
```

MS_Get_Indicators_V3.m

```
function [list]= MS_Get_Indicators_V3(SelectedProjectID)
global conn
%# Execute a SP from the DB...
cmd= exec(conn, ['EXEC SP_S_Indicators_V3 ''' SelectedProjectID '''']);
result = fetch(cmd);
list = result.data;
```

HandleControls_CalculateIndicators.m

```
function [ok]= HandleControls_CalculateIndicators(handles)

global handles_main CounterDesc_main SelectedProject_DetailID

WeatherON = get(handles.check_Weather, 'Value');

NonWeatherON = get(handles.check_NonWeather, 'Value');

clc

ok = false;

if (WeatherON)

   [Weekdays_C, Weekdays_B1Best, Weekdays_B2Best, Weekdays_B3Best, Weekdays_RMSMin1,Weekdays_RMSMin2, Weekdays_R2_1, Weekdays_R2_2 ...

      , Weekdays_p1Best, Weekdays_p2Best, Weekdays_Tmin, Weekdays_Tmax ...

      , Weekdays_TTest_1, Weekdays_FTest_1, Weekdays_TTest_2, Weekdays_FTest_2, Weekdays_MSE_1, Weekdays_MSE_2] ...

       = HandleControls_CalculateWeatherIndicators(handles_main, CounterDesc_main, true, '1');

   [Weekends_C, Weekends_B1Best, Weekends_B2Best, Weekends_B3Best, Weekends_RMSMin1,Weekends_RMSMin2, Weekends_R2_1, Weekends_R2_2 ...

      , Weekends_p1Best, Weekends_p2Best, Weekends_Tmin, Weekends_Tmax ...

      , Weekends_TTest_1, Weekends_FTest_1, Weekends_TTest_2, Weekends_FTest_2, Weekends_MSE_1, Weekends_MSE_2] ...

       = HandleControls_CalculateWeatherIndicators(handles_main, CounterDesc_main, true, '0');

   MS_Save_WeatherIndicators ...

       ( ...

           SelectedProject_DetailID ...

         , Weekdays_C, Weekdays_B1Best, Weekdays_B2Best, Weekdays_B3Best, Weekdays_RMSMin1,Weekdays_RMSMin2, Weekdays_R2_1, Weekdays_R2_2 ...
```

```
        , Weekdays_TTest_1.pval(1), Weekdays_TTest_1.pval(2), Weekdays_TTest_1.t(1), Weekdays_TTest_1.t(2), Weekdays_FTest_1.pval, Weekdays_FTest_1.f ...
        , Weekdays_TTest_2.pval(1), Weekdays_TTest_2.pval(2), Weekdays_TTest_2.t(1), Weekdays_TTest_2.t(2), Weekdays_FTest_2.pval, Weekdays_FTest_2.f ...
        , Weekdays_MSE_1, Weekdays_MSE_2 ...
        , Weekends_C, Weekends_B1Best, Weekends_B2Best, Weekends_B3Best, Weekends_RMSMin1,Weekends_RMSMin2, Weekends_R2_1, Weekends_R2_2 ...
        , Weekends_TTest_1.pval(1), Weekends_TTest_1.pval(2), Weekends_TTest_1.t(1), Weekends_TTest_1.t(2), Weekends_FTest_1.pval, Weekends_FTest_1.f ...
        , Weekends_TTest_2.pval(1), Weekends_TTest_2.pval(2), Weekends_TTest_2.t(1), Weekends_TTest_2.t(2), Weekends_FTest_2.pval, Weekends_FTest_2.f ...
        , Weekends_MSE_1, Weekends_MSE_2 ...
      )
   ok = true;
end
if (NonWeatherON)
   MS_Calculate_NonWeatherIndicators(SelectedProject_DetailID, '8','18', '22','6', '12','14')
   ok = true;
end
```

HandleControls_CalculateWeatherIndicators.m

```
function   [C, B1Best, B2Best, B3Best, RMSMin1,RMSMin2, R2_1Best, R2_2Best...
        , p1Best, p2Best, Tmin, Tmax, TTest_1BEST, FTest_1BEST...
        , TTest_2BEST, FTest_2BEST, MSE_1Best, MSE_2Best]...
```

```
= HandleControls_CalculateWeatherIndicators(handles, CounterDesc, RefreshData, WeekdaysSelected)

global SelectedProjectID

global DataToPlot

clc

if RefreshData

   hmsg= msgbox('Getting Data from db...','System message...','warn','non-modal');

Keyname= strtrim( CounterDesc(findstr(CounterDesc,'(')+1:findstr(CounterDesc,')')-1) );

   DataToPlot = MS_Get_EnergyVSTemperaturePlot(SelectedProjectID, Keyname, WeekdaysSelected);

   close(hmsg);

end

if strcmp(DataToPlot{1},'No Data')~=1

   TemperatureArray = cell2mat(DataToPlot(:,1));

   EnergyArray = cell2mat(DataToPlot(:,2));

   NumberPoints= length(TemperatureArray);

   Tmin = min(TemperatureArray);

   Tmax = max(TemperatureArray);

   X= (Tmax-Tmin)/10;

   B3= Tmin;

   B3= Tmin+ X;

   B3Best = B3;

   RMSMin = 1e20;

   for i=1:1:2

      while (B3<= Tmax-X)

         B3Where = find(TemperatureArray>=B3);
```

```
[p1,S1]= polyfit(TemperatureArray(1:B3Where(1)), EnergyArray(1:B3Where(1)), 1);

[p2,S2]= polyfit(TemperatureArray(B3Where(1):NumberPoints), EnergyArray(B3Where(1):NumberPoints), 1);

[RMS1, R2_1, TTest_1, FTest_1, MSE_1] = LinearRegressionFactor (TemperatureArray(1:B3Where(1)), EnergyArray(1:B3Where(1)), p1);

[RMS2, R2_2, TTest_2, FTest_2, MSE_2] = LinearRegressionFactor (TemperatureArray(B3Where(1):NumberPoints),
EnergyArray(B3Where(1):NumberPoints), p2);

RMS= RMS1+ RMS2;

if (RMS<RMSMin)

   B3Best = B3;

   B3WhereBest=B3Where;

   RMSMin = RMS;

   RMSMin1 = RMS1;

   RMSMin2 = RMS2;

   R2_1Best = R2_1;

   R2_2Best = R2_2;

   p1Best= p1;

   p2Best= p2;

   TTest_1BEST = TTest_1;

   FTest_1BEST = FTest_1;

   TTest_2BEST = TTest_2;

   FTest_2BEST = FTest_2;

   MSE_1Best= MSE_1;

   MSE_2Best= MSE_2;

end

B3= B3+ X;
```

```
        end
        B3 = Tmin;
        X= 2* X;
        B3= Tmin+ X;
    end
    B1Best= p1Best(1);
    B2Best= p2Best(1);
 %   B3Best= (p2Best(2)-p1Best(2))/(p1Best(1)-p2Best(1))
    if B3Best<Tmin
        B3Best= Tmin;
    end
    C= polyval(p1Best, B3Best);
else
    errordlg('No Data was found!')
end
%{
%plot data
    axes (handles.graph_Weather)
    hold off
    scatter(handles.graph_Weather, cell2mat(DataToPlot(:,1)), cell2mat(DataToPlot(:,2)),'.')
    xlabel('Temperature [C]');
    ylabel('Energy [kWh]');
    title(CounterDesc);
    hold on
    int= (Tmax-Tmin)/100;
    x1= [Tmin:int:B3Best];
    x2= [B3Best:int:Tmax];
```

```
    plot(x1, polyval(p1Best,x1), 'red');
    plot(x2, polyval(p2Best,x2), 'green');
%}
```

MS_Save_WeatherIndicators.m

```
function MS_Save_WeatherIndicators ...
    ( ...
        SelectedProject_DetailID ...
        , Weekdays_C, Weekdays_B1Best, Weekdays_B2Best, Weekdays_B3Best, Weekdays_RMSMin1,Weekdays_RMSMin2, Weekdays_R2_1, Weekdays_R2_2 ...
        , Weekdays_TTest_1_pval_C, Weekdays_TTest_1_pval_m, Weekdays_TTest_1_t_C, Weekdays_TTest_1_t_m, Weekdays_FTest_1_pval, Weekdays_FTest_1_f ...
        , Weekdays_TTest_2_pval_C, Weekdays_TTest_2_pval_m, Weekdays_TTest_2_t_C, Weekdays_TTest_2_t_m, Weekdays_FTest_2_pval, Weekdays_FTest_2_f ...
        , Weekdays_MSE_1, Weekdays_MSE_2 ...
        , Weekends_C, Weekends_B1Best, Weekends_B2Best, Weekends_B3Best, Weekends_RMSMin1,Weekends_RMSMin2, Weekends_R2_1, Weekends_R2_2 ...
        , Weekends_TTest_1_pval_C, Weekends_TTest_1_pval_m, Weekends_TTest_1_t_C, Weekends_TTest_1_t_m, Weekends_FTest_1_pval, Weekends_FTest_1_f ...
        , Weekends_TTest_2_pval_C, Weekends_TTest_2_pval_m, Weekends_TTest_2_t_C, Weekends_TTest_2_t_m, Weekends_FTest_2_pval, Weekends_FTest_2_f ...
        , Weekends_MSE_1, Weekends_MSE_2 ...
    )
global conn
clc
```

```
%# Execute a SP from the DB...

sql= [];

sql = [sql 'EXEC SP_I_Indicator_Weather ''' num2str(SelectedProject_DetailID) ''',''' num2str(Weekdays_C) ''',''' num2str(Weekdays_B1Best) ''',''' num2str(Weekdays_B2Best) ''',''' num2str(Weekdays_B3Best) ''',''' num2str(Weekdays_RMSMin1) ''',''' num2str(Weekdays_RMSMin2) ''',''' num2str(Weekdays_R2_1) ''',''' num2str(Weekdays_R2_2)];

sql = [sql ''',''' num2str(Weekdays_TTest_1_pval_C) ''',''' num2str(Weekdays_TTest_2_pval_C) ''',''' num2str(Weekdays_TTest_1_pval_m) ''',''' num2str(Weekdays_TTest_2_pval_m) ''',''' num2str(Weekdays_TTest_1_t_C) ''',''' num2str(Weekdays_TTest_2_t_C) ''',''' num2str(Weekdays_TTest_1_t_m) ''',''' num2str(Weekdays_TTest_2_t_m) ];

sql = [sql ''',''' num2str(Weekdays_FTest_1_pval) ''',''' num2str(Weekdays_FTest_2_pval) ''',''' num2str(Weekdays_FTest_1_f) ''',''' num2str(Weekdays_FTest_2_f) ''',''' num2str(Weekdays_MSE_1) ''',''' num2str(Weekdays_MSE_2) ];

sql = [sql ''',''' num2str(Weekends_C) ''',''' num2str(Weekends_B1Best) ''',''' num2str(Weekends_B2Best) ''',''' num2str(Weekends_B3Best) ''',''' num2str(Weekends_RMSMin1) ''',''' num2str(Weekends_RMSMin2) ''',''' num2str(Weekends_R2_1) ''',''' num2str(Weekends_R2_2) ];

sql = [sql ''',''' num2str(Weekends_TTest_1_pval_C) ''',''' num2str(Weekends_TTest_2_pval_C) ''',''' num2str(Weekends_TTest_1_pval_m) ''',''' num2str(Weekends_TTest_2_pval_m) ''',''' num2str(Weekends_TTest_1_t_C) ''',''' num2str(Weekends_TTest_2_t_C) ''',''' num2str(Weekends_TTest_1_t_m) ''',''' num2str(Weekends_TTest_2_t_m) ];

sql = [sql ''',''' num2str(Weekends_FTest_1_pval) ''',''' num2str(Weekends_FTest_2_pval) ''',''' num2str(Weekends_FTest_1_f) ''',''' num2str(Weekends_FTest_2_f) ''',''' num2str(Weekends_MSE_1) ''',''' num2str(Weekends_MSE_2)  '''' ];

sql

cmd= exec(conn, sql);
```

MS_Calculate_NonWeatherIndicators.m

```
function MS_Calculate_NonWeatherIndicators(SelectedProject_DetailID, DayStartHour,DayEndHour, NightStartHour,NightEndHour, LunchStartHour,LunchEndHour)

global conn

clc

%# Execute a SP from the DB...

sql=['EXEC SP_I_Indicator_NonWeather_V2 ''' num2str(SelectedProject_DetailID) ''',''' DayStartHour ''',''' DayEndHour ''',''' NightStartHour ''',''' NightEndHour ''',''' LunchStartHour ''',''' LunchEndHour '''']

cmd= exec(conn, sql);
```

HandleControls_InitiateViewNonWeather.m

```
function [no]= HandleControls_InitiateViewNonWeather(handles, CounterDesc, RefreshData)

global SelectedProjectID

global DataToPlot

clc

WeekdaysSelected = num2str(HandleControls_GetRadioValueTypeDayList(handles));

WeekdaySelected_Name = HandleControls_GetRadioValueNameDayList(handles);

if RefreshData

   hmsg= msgbox('Getting Data from db...','System message...','warn','non-modal');

   Keyname= strtrim( CounterDesc(findstr(CounterDesc,'(')+1:findstr(CounterDesc,')')-1) );

   DataToPlot = MS_Get_AverageDailyPlot(SelectedProjectID, Keyname, WeekdaysSelected);

   close(hmsg)

end

if strcmp(DataToPlot{1},'No Data')~=1
```

```
BWM_on = get(handles.check_BWM, 'Value');
MinMax_on = get(handles.check_MinMax, 'Value');
axes (handles.graph_NonWeather)
hold off
plot(handles.graph_NonWeather, cell2mat(DataToPlot(:,1)), cell2mat(DataToPlot(:,2)), 'blue')
xlabel('Time [hour]');
ylabel('Energy [kWh]');
title([CounterDesc ' - ' WeekdaySelected_Name]);
if BWM_on== 1
    hold on
    %% STDev
    plot(handles.graph_NonWeather, cell2mat(DataToPlot(:,1)), cell2mat(DataToPlot(:,3)), 'yellow')
    %% P10, P90
    plot(handles.graph_NonWeather, cell2mat(DataToPlot(:,1)), cell2mat(DataToPlot(:,6)), 'color','black','linestyle', ':')
    plot(handles.graph_NonWeather, cell2mat(DataToPlot(:,1)), cell2mat(DataToPlot(:,10)), 'color','black','linestyle', ':')
    %% P25, P75
    plot(handles.graph_NonWeather, cell2mat(DataToPlot(:,1)), cell2mat(DataToPlot(:,7)), 'color','black','linestyle', '-.')
    plot(handles.graph_NonWeather, cell2mat(DataToPlot(:,1)), cell2mat(DataToPlot(:,9)), 'color','black','linestyle', '-.')
    %% P50
    plot(handles.graph_NonWeather, cell2mat(DataToPlot(:,1)), cell2mat(DataToPlot(:,8)), 'color','black','linestyle', '--')
end
```

```
    if MinMax_on== 1
        hold on
        %% Min
        plot(handles.graph_NonWeather,                    cell2mat(DataToPlot(:,1)),
cell2mat(DataToPlot(:,4)), 'green')
        %% Max
        plot(handles.graph_NonWeather,                    cell2mat(DataToPlot(:,1)),
cell2mat(DataToPlot(:,5)), 'red')
    end
    xlim([0 24]);
    set(handles.graph_NonWeather,'XTick',[0 6 12 18 24])
    if BWM_on & MinMax_on
        legend(handles.graph_NonWeather, 'Average                    .', 'Standard
Deviation', '10th Percentil', '90th Percentil', '25th Percentil', '75th Percentil', '50th Percentil',
'Minimum', 'Maximum', 'Location','Best');
    elseif BWM_on
        legend(handles.graph_NonWeather, 'Average                    .', 'Standard
Deviation', '10th Percentil', '90th Percentil', '25th Percentil', '75th Percentil', '50th Percentil',
'Location','Best');
    elseif MinMax_on
        legend(handles.graph_NonWeather, 'Average                    .', 'Minimum',
'Maximum', 'Location','Best');
    else
        legend(handles.graph_NonWeather,  'Average                              .',
'Location','Best');
    end
else
    errordlg('No Data was found!')
```

end

MS_Get_AverageDailyPlot.m

```
function [list] = MS_Get_AverageDailyPlot(ProjectID, Keyname,DaysToList)

global conn

clc

%# Execute a SP from the DB...

sql=['EXEC SP_S_data_process_NonWeatherProfile_V2 ''' ProjectID ''',''' Keyname ''',''' DaysToList '''']

cmd= exec(conn, sql);

result = fetch(cmd);

list = result.data;
```

HandleControls_InitiateViewWeather.m

```
function [no]= HandleControls_InitiateViewWeather(handles, CounterDesc, RefreshData)

global SelectedProjectID

global DataToPlot

clc

WeekdaysSelected = num2str(HandleControls_GetRadioValueTypeDayList_Weather(handles));

BestfitON = get(handles.check_Bestfit, 'Value');

WeekdaySelected_Name = HandleControls_GetRadioValueNameDayList_Weather(handles);

if RefreshData

   hmsg= msgbox('Getting Data from db...','System message...','warn','non-modal');

   Keyname= strtrim( CounterDesc(findstr(CounterDesc,'(')+1:findstr(CounterDesc,')')-1) );
```

```
  DataToPlot = MS_Get_EnergyVSTemperaturePlot(SelectedProjectID, Keyname,
WeekdaysSelected)
  close(hmsg)
end
RefreshData
if strcmp(DataToPlot{1},'No Data')~=1
  axes (handles.graph_Weather)
  hold off
  scatter(handles.graph_Weather, cell2mat(DataToPlot(:,1)), cell2mat(DataToPlot(:,2)),'.')
  xlabel('Temperature [C]');
  ylabel('Energy [kWh]');
  title([CounterDesc ' - ' WeekdaySelected_Name]);
else
  errordlg('No Data was found!', 'System message...')
end
if BestfitON
  [C, B1Best, B2Best, B3Best, RMSMin1,RMSMin2, R2_1, R2_2, p1Best, p2Best, Tmin,
Tmax...
   , TTest_1BEST, FTest_1BEST, TTest_2BEST, FTest_2BEST] ...
     = HandleControls_CalculateWeatherIndicators(handles, CounterDesc, RefreshData,
WeekdaysSelected);
  %plot data
  axes (handles.graph_Weather)
  hold on
  int= (Tmax-Tmin)/100;
  x1= [Tmin:int:B3Best];
  x2= [B3Best:int:Tmax];
```

```
    plot(x1, polyval(p1Best,x1), 'red');
    plot(x2, polyval(p2Best,x2), 'green');
end
```

MS_Get_EnergyVSTemperaturePlot.m

```
function [list] = MS_Get_EnergyVSTemperaturePlot(ProjectID, Keyname,DaysToList)
global conn
clc
%# Execute a SP from the DB...
sql=['EXEC SP_S_data_process_WeatherProfile_V3 ''' ProjectID ''',''' Keyname ''',''' DaysToList ''''];
cmd= exec(conn, sql);
result = fetch(cmd);
list = result.data;
```

HandleControls_CalculateWeatherIndicators.m

```
function [C, B1Best, B2Best, B3Best, RMSMin1,RMSMin2, R2_1Best, R2_2Best...
        , p1Best, p2Best, Tmin, Tmax, TTest_1BEST, FTest_1BEST...
        , TTest_2BEST, FTest_2BEST, MSE_1Best, MSE_2Best]...
        = HandleControls_CalculateWeatherIndicators(handles, CounterDesc, RefreshData, WeekdaysSelected)
global SelectedProjectID
global DataToPlot
clc
if RefreshData
    hmsg= msgbox('Getting Data from db...','System message...','warn','non-modal');
    Keyname= strtrim( CounterDesc(findstr(CounterDesc,'(')+1:findstr(CounterDesc,')')-1) );
```

```
    DataToPlot = MS_Get_EnergyVSTemperaturePlot(SelectedProjectID, Keyname, WeekdaysSelected);
    close(hmsg);
end
if strcmp(DataToPlot{1},'No Data')~=1
    TemperatureArray = cell2mat(DataToPlot(:,1));
    EnergyArray = cell2mat(DataToPlot(:,2));
    NumberPoints= length(TemperatureArray);
    Tmin = min(TemperatureArray);
    Tmax = max(TemperatureArray);
    X= (Tmax-Tmin)/10;
    B3= Tmin;
    B3= Tmin+ X;
    B3Best = B3;
    RMSMin = 1e20;
    for i=1:1:2
        while (B3<= Tmax-X)
            B3Where = find(TemperatureArray>=B3);
            [p1,S1]= polyfit(TemperatureArray(1:B3Where(1)), EnergyArray(1:B3Where(1)), 1);
            [p2,S2]= polyfit(TemperatureArray(B3Where(1):NumberPoints), EnergyArray(B3Where(1):NumberPoints), 1);
            [RMS1, R2_1, TTest_1, FTest_1, MSE_1] = LinearRegressionFactor (TemperatureArray(1:B3Where(1)), EnergyArray(1:B3Where(1)), p1);
            [RMS2, R2_2, TTest_2, FTest_2, MSE_2] = LinearRegressionFactor (TemperatureArray(B3Where(1):NumberPoints), EnergyArray(B3Where(1):NumberPoints), p2);
            RMS= RMS1+ RMS2;
```

```
        if (RMS<RMSMin)
            B3Best = B3;
            B3WhereBest=B3Where;
            RMSMin = RMS;
            RMSMin1 = RMS1;
            RMSMin2 = RMS2;
            R2_1Best = R2_1;
            R2_2Best = R2_2;
            p1Best= p1;
            p2Best= p2;
            TTest_1BEST = TTest_1;
            FTest_1BEST = FTest_1;
            TTest_2BEST = TTest_2;
            FTest_2BEST = FTest_2;
            MSE_1Best= MSE_1;
            MSE_2Best= MSE_2;
        end
        B3= B3+ X;
    end
    B3 = Tmin;
    X= 2* X;
    B3= Tmin+ X;
end
 B1Best= p1Best(1);
 B2Best= p2Best(1);
 B3Best= (p2Best(2)-p1Best(2))/(p1Best(1)-p2Best(1))
 if B3Best<Tmin
```

```
        B3Best= Tmin;
    end
    C= polyval(p1Best, B3Best);
else
    errordlg('No Data was found!')
end
%{
    %plot data
    axes (handles.graph_Weather)
    hold off
    scatter(handles.graph_Weather, cell2mat(DataToPlot(:,1)), cell2mat(DataToPlot(:,2)),'.')
    xlabel('Temperature [C]');
    ylabel('Energy [kWh]');
    title(CounterDesc);
    hold on
    int= (Tmax-Tmin)/100;
    x1= [Tmin:int:B3Best];
    x2= [B3Best:int:Tmax];
    plot(x1, polyval(p1Best,x1), 'red');
    plot(x2, polyval(p2Best,x2), 'green');
%}
```

HandleControls_InitiateView3D.m

```
function [no]= HandleControls_InitiateView3D(handles, CounterDesc, RefreshData)
global SelectedProjectID
global DataToPlot
clc
```

```
WeekdaysSelected = '-1';
if RefreshData
    hmsg= msgbox('Getting Data from db...','System message...','warn','non-modal');
    Keyname= strtrim( CounterDesc(findstr(CounterDesc,'(')+1:findstr(CounterDesc,')')-1) );
    DataToPlot = MS_Get_SurfaceChart_V2(SelectedProjectID, Keyname,
WeekdaysSelected);
    close(hmsg)
end
if strcmp(DataToPlot{1},'No Data')~=1
    NumberCol= size(DataToPlot,2);
    Matrix= cell2mat(DataToPlot(:, 4:NumberCol));
    axes (handles.graph_3D)
    hold off
    surf(Matrix, 'EdgeColor', 'none')
    if get(handles.radio_2D, 'Value')== 1
        view(2);
    else
        view(3);
    end
    xlabel('Time [hour]');
    NumberX = size(Matrix, 2);
    set(gca,'XTick',[1 NumberX/4 NumberX/2 3*NumberX/4 NumberX])
    set(gca,'XTickLabel','0|6|12|18|24')
    ylabel('Time [day]');
    NumberY = size(Matrix, 1);
    set(gca,'YTick',[1 NumberY/4 NumberY/2 3*NumberY/4 NumberY])
```

```
    L1 = [num2str(DataToPlot{1, 1}) '/' num2str(DataToPlot{1, 2}) '/' num2str(DataToPlot{1, 3})];
    L2 = [num2str(DataToPlot{round(NumberY/4), 1}) '/' num2str(DataToPlot{round(NumberY/4), 2}) '/' num2str(DataToPlot{round(NumberY/4), 3})];
    L3 = [num2str(DataToPlot{round(NumberY/2), 1}) '/' num2str(DataToPlot{round(NumberY/2), 2}) '/' num2str(DataToPlot{round(NumberY/2), 3})];
    L4 = [num2str(DataToPlot{round(3*NumberY/4), 1}) '/' num2str(DataToPlot{round(3*NumberY/4), 2}) '/' num2str(DataToPlot{round(3*NumberY/4), 3})];
    L5 = [num2str(DataToPlot{round(NumberY), 1}) '/' num2str(DataToPlot{round(NumberY), 2}) '/' num2str(DataToPlot{round(NumberY), 3})];
    set(gca,'YTickLabel',[L1 '|' L2 '|' L3 '|' L4 '|' L5])
    zlabel('Energy [kWh]');
    title(CounterDesc);
    colorbar();
else
    errordlg('No Data was found!', 'System message...')
end
%{
clc
WeekdaysSelected = '-1';
if RefreshData
    hmsg= msgbox('Getting Data from db...','System message...','warn','non-modal');
    Keyname= strtrim( CounterDesc(findstr(CounterDesc,'(')+1:findstr(CounterDesc,')')-1) );
    DataToPlot = MS_Get_SurfaceChart(SelectedProjectID, Keyname, WeekdaysSelected);
    close(hmsg)
```

```
end
if strcmp(DataToPlot{1},'No Data')~=1
    Matrix= HandleControls_CreateSurfaceChartMatrix(DataToPlot);
    axes (handles.graph_3D)
    hold off
    scatter3(Matrix(:,1), Matrix(:,2),Matrix(:,3), 5,Matrix(:,3), 'filled')
    if get(handles.radio_2D, 'Value')== 1
        view(2);
    else
        view(3);
    end
    xlabel('Time [day]');
    ylabel('Time [hour]');
    zlabel('Energy [kWh]');
    title(CounterDesc);
else
    errordlg('No Data was found!', 'System message...')
end
%}
```

MS_Get_SurfaceChart_V2.m

```
function [list] = MS_Get_SurfaceChart_V2(ProjectID, Keyname,DaysToList)
global conn
clc
%# Execute a SP from the DB...
sql=['EXEC SP_S_data_process_SurfaceChart_V2 ''' ProjectID ''',''' Keyname ''',''' DaysToList '''']
```

```
cmd= exec(conn, sql);

result = fetch(cmd);

list = result.data;
```

HandleControls_InitiateViewDailyTotals.m

```
function [no]= HandleControls_InitiateViewDailyTotals(handles, CounterDesc, RefreshData)

global SelectedProjectID

global DataToPlot

clc

TypeGroupSelected =HandleControls_GetRadioValueTypeGroupList(handles);

TypeGroupSelected_Name = HandleControls_GetRadioValueNameGroupList(handles);

if RefreshData

   hmsg= msgbox('Getting Data from db...','System message...','warn','non-modal');

   Keyname= strtrim( CounterDesc(findstr(CounterDesc,'(')+1:findstr(CounterDesc,')')-1) );

   if TypeGroupSelected== 3

      DataToPlot = MS_Get_DailyTotals_Daily(SelectedProjectID, Keyname);

   elseif TypeGroupSelected== 2

      DataToPlot = MS_Get_DailyTotals_Weekly(SelectedProjectID, Keyname);

   elseif TypeGroupSelected== 1

      DataToPlot = MS_Get_DailyTotals_Monthly(SelectedProjectID, Keyname);

   end

   close(hmsg)

end

if strcmp(DataToPlot{1},'No Data')~=1

   BWM_on = get(handles.check_DTBWM, 'Value');

   MinMax_on = get(handles.check_DTMinMax, 'Value');
```

```
axes (handles.graph_DailyTotals)
hold off
plot(handles.graph_DailyTotals, cell2mat(DataToPlot(:,1)), cell2mat(DataToPlot(:,2)), 'blue')
if BWM_on== 1 & TypeGroupSelected~= 3
    hold on
    %% STDev
    plot(handles.graph_DailyTotals, cell2mat(DataToPlot(:,1)), cell2mat(DataToPlot(:,3)), 'yellow')
    %% P10, P90
    plot(handles.graph_DailyTotals, cell2mat(DataToPlot(:,1)), cell2mat(DataToPlot(:,6)), 'color','black','linestyle', ':')
    plot(handles.graph_DailyTotals, cell2mat(DataToPlot(:,1)), cell2mat(DataToPlot(:,10)), 'color','black','linestyle', ':')
    %% P25, P75
    plot(handles.graph_DailyTotals, cell2mat(DataToPlot(:,1)), cell2mat(DataToPlot(:,7)), 'color','black','linestyle', '-.')
    plot(handles.graph_DailyTotals, cell2mat(DataToPlot(:,1)), cell2mat(DataToPlot(:,9)), 'color','black','linestyle', '-.')
    %% P50
    plot(handles.graph_DailyTotals, cell2mat(DataToPlot(:,1)), cell2mat(DataToPlot(:,8)), 'color','black','linestyle', '--')
end
if MinMax_on== 1 & TypeGroupSelected~= 3
    hold on
    %% Min
    plot(handles.graph_DailyTotals, cell2mat(DataToPlot(:,1)), cell2mat(DataToPlot(:,4)), 'green')
```

```
        %% Max
        plot(handles.graph_DailyTotals, cell2mat(DataToPlot(:,1)), cell2mat(DataToPlot(:,5)),
'red')
    end
    if TypeGroupSelected== 3
        xlim([1 366]);
        xlabel('Days');
        ylabel('Energy - Daily Total [kWh]');
        title([CounterDesc ' - Day']);
    elseif TypeGroupSelected== 2
        xlim([1 52]);
        xlabel('Weeks');
        ylabel('Energy - Daily Average [kWh]');
        title([CounterDesc ' - Week']);
    elseif TypeGroupSelected== 1
        xlim([1 12]);
        xlabel('Months');
        ylabel('Energy - Daily Average [kWh]');
        title([CounterDesc ' - Month']);
    end
    if BWM_on & MinMax_on & TypeGroupSelected~= 3
        legend(handles.graph_DailyTotals, 'Average                                    .', 'Standard
Deviation', '10th Percentil', '90th Percentil', '25th Percentil', '75th Percentil', '50th Percentil',
'Minimum', 'Maximum', 'Location','Best');
    elseif BWM_on & TypeGroupSelected~= 3
        legend(handles.graph_DailyTotals, 'Average                                    .', 'Standard
Deviation', '10th Percentil', '90th Percentil', '25th Percentil', '75th Percentil', '50th Percentil',
'Location','Best');
```

```
    elseif MinMax_on & TypeGroupSelected~= 3
        legend(handles.graph_DailyTotals, 'Average                                   .', 'Minimum',
'Maximum', 'Location','Best');
    elseif  TypeGroupSelected~= 3
        legend(handles.graph_DailyTotals,  'Average                                              .',
'Location','Best');
    else
        legend(off);
    end
else
    errordlg('No Data was found!')
end
```

MS_Get_DailyTotals_Daily.m

```
function [list] = MS_Get_DailyTotals_Daily(ProjectID, Keyname)
global conn
clc
%# Execute a SP from the DB...
sql=['EXEC SP_S_data_process_DailyTotals_Daily '''  ProjectID  ''',''' Keyname    '''']
cmd= exec(conn, sql);
result = fetch(cmd);
list = result.data;
```

MS_Get_DailyTotals_Monthly.m

```
function [list] = MS_Get_DailyTotals_Monthly(ProjectID, Keyname)
global conn
clc
```

```
%# Execute a SP from the DB...

sql=['EXEC SP_S_data_process_DailyTotals_Monthly '''  ProjectID  ''',''' Keyname    '''']

cmd= exec(conn, sql);

result = fetch(cmd);

list = result.data;
```

MS_Get_DailyTotals_Weekly.m

```
function [list] = MS_Get_DailyTotals_Weekly(ProjectID, Keyname)

global conn

clc

%# Execute a SP from the DB...

sql=['EXEC SP_S_data_process_DailyTotals_Weekly '''  ProjectID  ''',''' Keyname    '''']

cmd= exec(conn, sql);

result = fetch(cmd);

list = result.data;
```

Appendix C – Papers published

Ferreira, V. and Fleming, P. (2009) Evaluation of water and energy metering and monitoring practices in European local authorities. ECEEE Summer Study 2009. Cote D'azur.

Vasco Ferreira, 3183

Evaluation of water and energy metering and monitoring practices in European local authorities

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Keywords

Energy, water, survey, practices, metering, monitoring, European local authorities, municipal buildings, efficiency, EPBD Directive, ESCO Directive

Abstract

Metering and monitoring building water and energy consumption is becoming an increasingly important activity in European municipalities as a tool to improve building energy efficiency. This paper presents the results of a survey to European local authorities carried out to investigate metering, monitoring and energy management practices in European municipal buildings. The respondents were informed about the survey through different European networks of cities and municipalities active in sustainability, climate change and energy issues, such as Energie-Cites, ICLEI-Europe and CEMR. The survey had a total of 76 respondents from 19 European countries, responsible for managing energy and/or water consumption in over 63,000 municipal buildings. It was found that nearly all the European local authorities represented in the study are collecting data on building water, electricity and gas consumption. This data is collected both manually and automatically and is being used to identify and quantify energy savings. However, energy managers are using relatively simple analytical and visualisation techniques to analyse the data. The survey showed that there is a demand for more automated, accurate and flexible metering, and for easy-to-use water and energy consumption monitoring tools and techniques.

Survey planning, preparation and delivery

Short time series (hourly and sub-hourly frequencies) metering hardware is becoming less expensive and the need for more accurate billing in the new liberalised energy markets is driving the increasing availability of such 'smart' metering. Short-time series data for a large number of buildings and sites is now available and can be analysed using different data analysis software techniques to manage energy and water consumption in buildings. The recently approved Directive on End-Use Efficiency and Energy Services is also an important driver for the development of new metering and monitoring practices for improved energy efficiency in the European Union. Article 13 of the Directive requires Member States to ensure that meters and systems measure the actual energy consumption, both accurately and frequently. Energy users should have access to good quality and frequent billing information. This is expected to have an impact in delivering energy savings. However, there are also other potential applications for intelligent metering, in particular for grid management and demand side management. Continuous monitoring and performance assessment can quantify and verify energy savings following corrective actions or the implementation of energy efficiency measures.

More than 300 buildings owned by Leicester City Council are being monitored using an automatic metering and monitoring system. This system has been the basis for research and development of new energy analysis techniques (Ferreira et. al 2006 and 2007). EC Intelligent Energy Programme, supported two projects on metering and monitoring municipal building energy use: Intelligent Metering (Webber et. al, 2007) and ENERinTOWN (Ferreira et. al, 2007) projects. Both projects assessed the technical and non-technical barriers of deploying metering and monitoring system in complex institutions such as local authorities. These projects involved more than 30 municipalities in Europe for about 11 different countries, which demonstrates the increasing interest of local authorities to manage their energy costs by installing automatic metering and monitoring systems.

This paper describes a survey of European Municipalities to assess their metering and monitoring practices. It was based on an exploratory survey, aimed at investigating how metering and monitoring in municipal buildings is currently being carried out in European local authorities. It also assessed the energy managers' needs in terms of data technology hardware and software.

The survey was conducted through an online questionnaire distributed to European energy managers. This was the considered the most appropriate and feasible way to collect information on building energy and water metering and monitoring practices. The survey questions were devised and analysed based on previous survey research. (Converse et al., 1986) and (Reeves et al., 1981) state that in an exploratory qualitative study error margins are not the key issue, and that sample size only needed to be large enough to ensure a wide variety of answers from different countries. Therefore 20 to 30 replies might be enough to get qualitative information on the metering and monitoring practices in European local authorities. All the answers were from voluntary respondents who were informed about the survey through different European networks of cities and municipalities active in sustainability, climate change and energy issues, such as Energie-Cites (www.energie-cites.org), the European office of ICLEI - Local Governments for Sustainability (www.iclei-europe.org) and CEMR, the Council of European Municipalities and Regions (www.ccre.org). Therefore the local authorities that responded to this survey can be considered very active in energy management, when compared to other European local authorities. Consequently the results presented here are biased, and may be considered to be amongst the best practice in Europe.

The survey questionnaire was devised and then piloted in late August until early October 2006. Three local authorities (from UK, Germany and Spain) and Energie-Cités took part in the pilot exercise and the survey was amended to take into account the views of the pilot respondents. The main online questionnaire was available at: http://www.iesd.dmu.ac.uk/survey/emb/. The survey started on the 13th of November 2006 and was closed on the 31st of January 2008. During this period several emails were sent to energy managers, directly by the authors and by the networks: Energie-Cités, ICLEI-Europe and CEMR.

The survey had 76 respondents in total, from 19 European countries, as presented in Figure 1. About 39% of the respondents were from the UK, this because the questionnaire was only available in English and not in other languages. In total, the respondents said to be responsible for managing energy and/or water consumption in nearly 63 thousand municipal buildings.

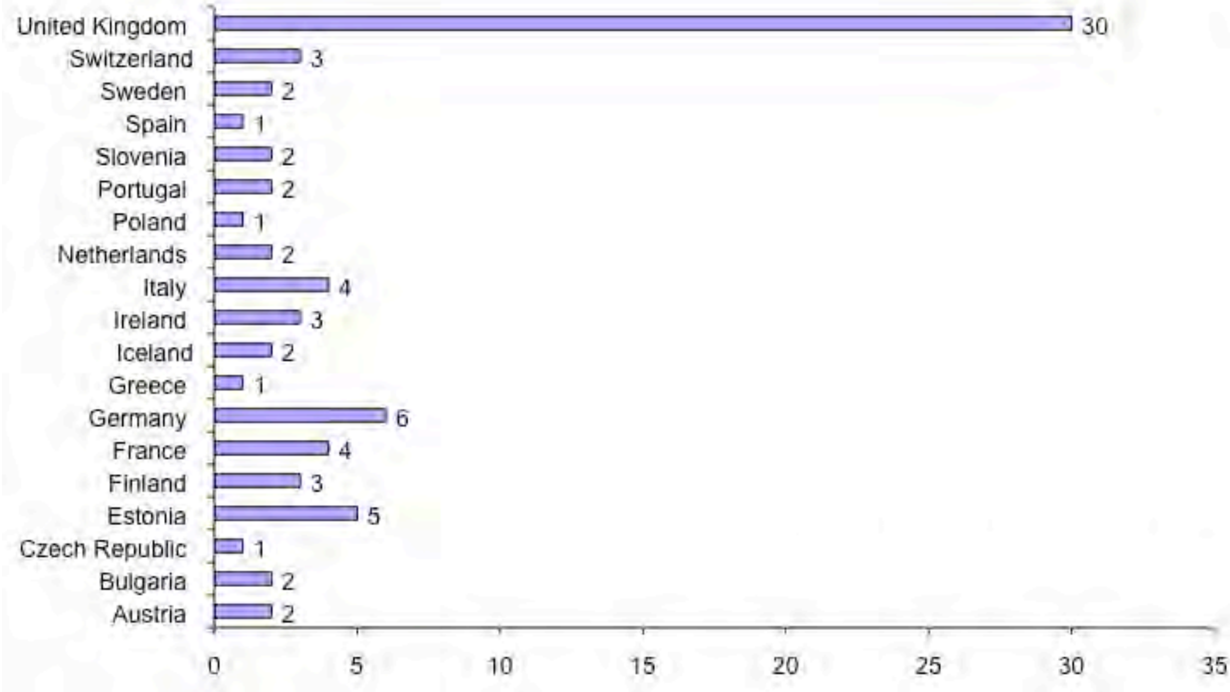

Figure 1. Number of respondents per country

Data collection practices by local authorities

It was found that most (nearly all municipalities in the study) European municipalities are collecting data in municipal buildings related to the use of water, electricity and gas consumption. As expected, electricity consumption data is collected in most of the municipalities (71 out of the 76 municipalities), followed by water consumption data (65 out of the 76 municipalities) and gas consumption data (62 out of the 76 municipalities).

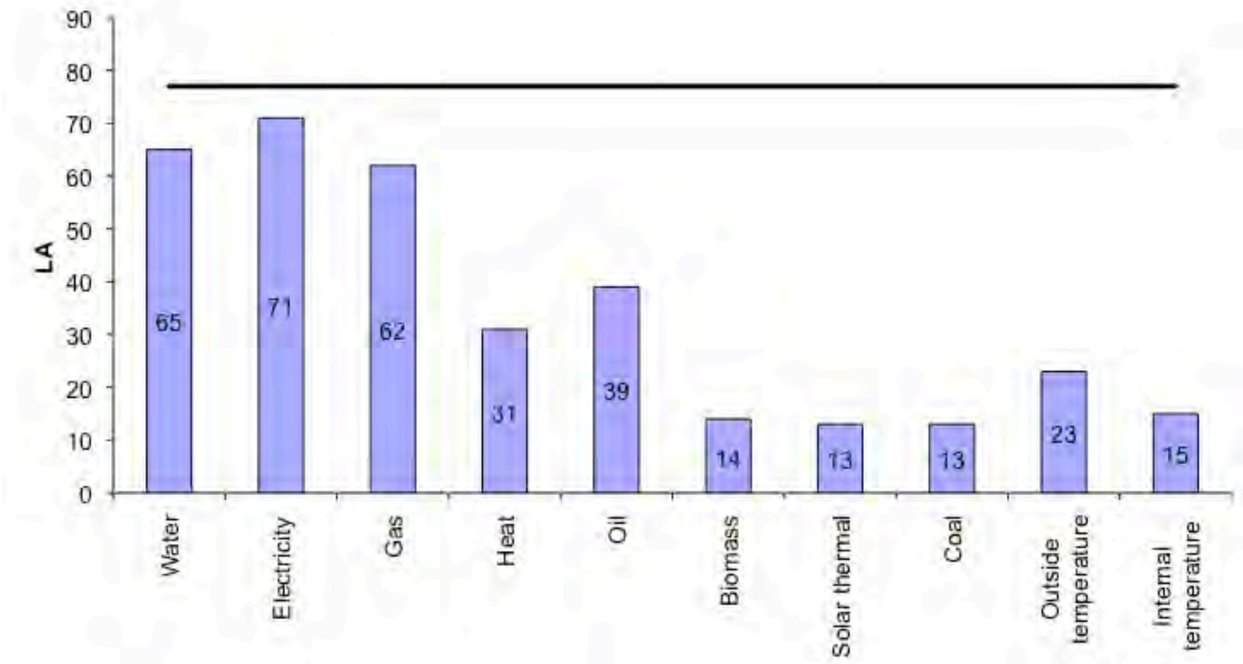

Figure 2. Number of European local authorities collecting water and energy data being

Data on oil use, for space heating systems, is collected in more than 50% of the local authorities that replied to the survey, and heat use is collected in 1/3 of the municipalities that participated in the study. Additionally, 30% of the municipalities are collecting outside temperature data. Biomass, solar thermal and coal consumption data are only collected in a few municipalities, since they are not very common energy sources in European municipal buildings.

Building internal temperature data is collected in very few local authorities, mostly in large buildings with building energy management systems (BEMS).

From Figure 3 it is possible to see that only a relatively small proportion of municipalities collect building data automatically through electronic bills, and even less with automatic metering systems.

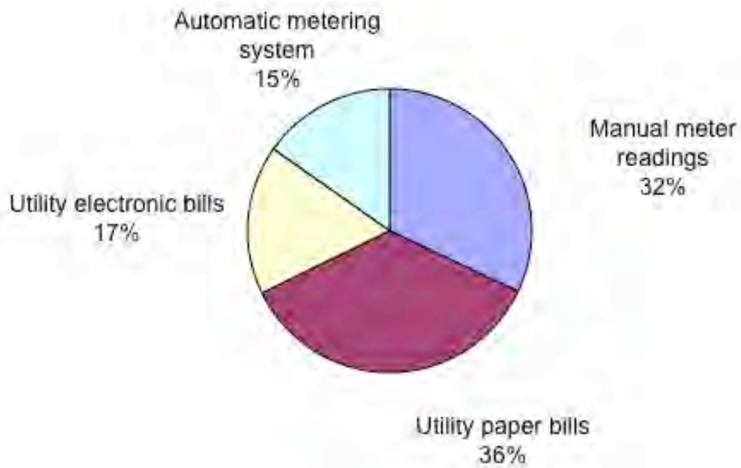

Figure 3. Data collection procedures used by local authorities

About 32% of the energy and water data is being collected through manual meter readings, and about 36%, through utility paper bills. European municipalities are still using manual and very little sophisticated procedures to collect energy and water data. Electronic bills provided by utilities are only responsible for about 17% of the data collected, and automatic metering reading system represent just 15% of the data collected.

Figure 4 presents a breakdown of data collection procedures per type of utility: water, electricity, gas, etc. Automatic metering systems are responsible for collecting water, electricity and gas in 10%, 13% and 7% of the cases, respectively. However, automatic systems are being used to monitor the new and renewable energy use: 21% for heat and 47% for solar thermal. Temperature data is also being collected automatically: 63% outside temperature and 53% for inside temperature. There is no additional information on utilities referred to on the 'Other' category. Nevertheless and from the results in other questions these replies are probably referring to degree-day information collection.

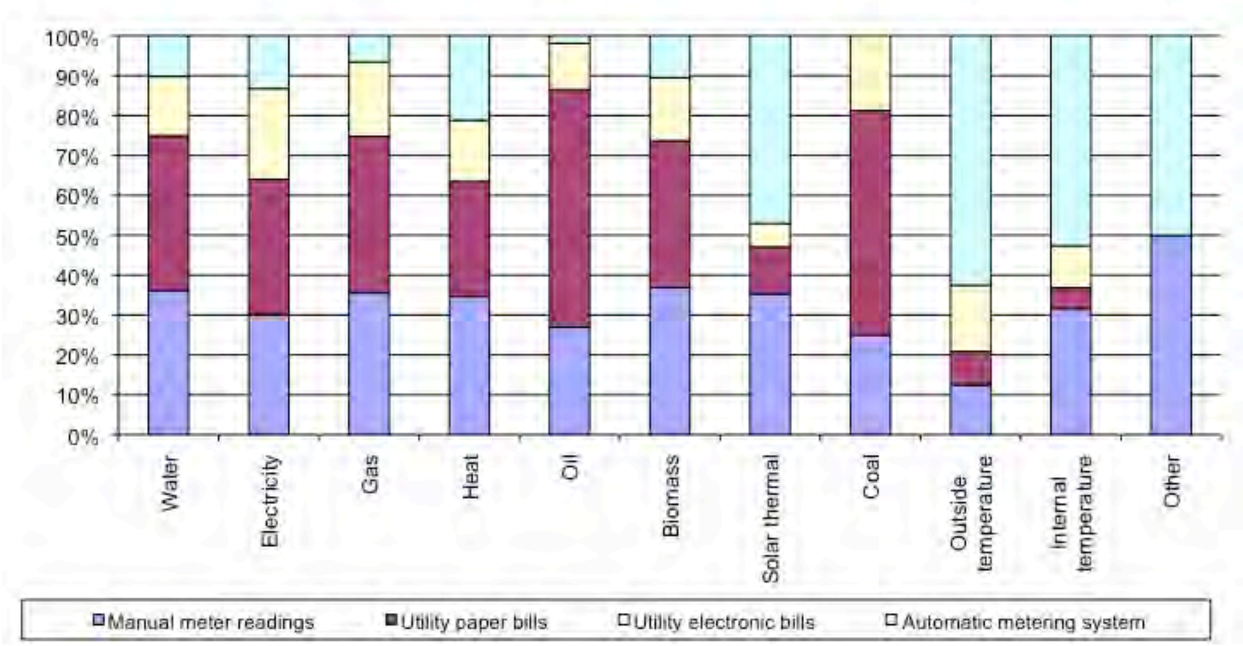

Figure 4. Type of water and energy data collection procedure per utility

It was found that monthly data collection frequency is used for about 35% of the cases. Data collected in periods larger than the month (in which we included intermittently collected data) represent 41% of all data. Only about 12% of the data is collected in sub-daily periods, i.e. in half-hourly (or less) intervals.

Figure 5 presents the frequency of data collection for each utility. From half-hourly or less, daily, weekly, monthly to data being collected intermittently.

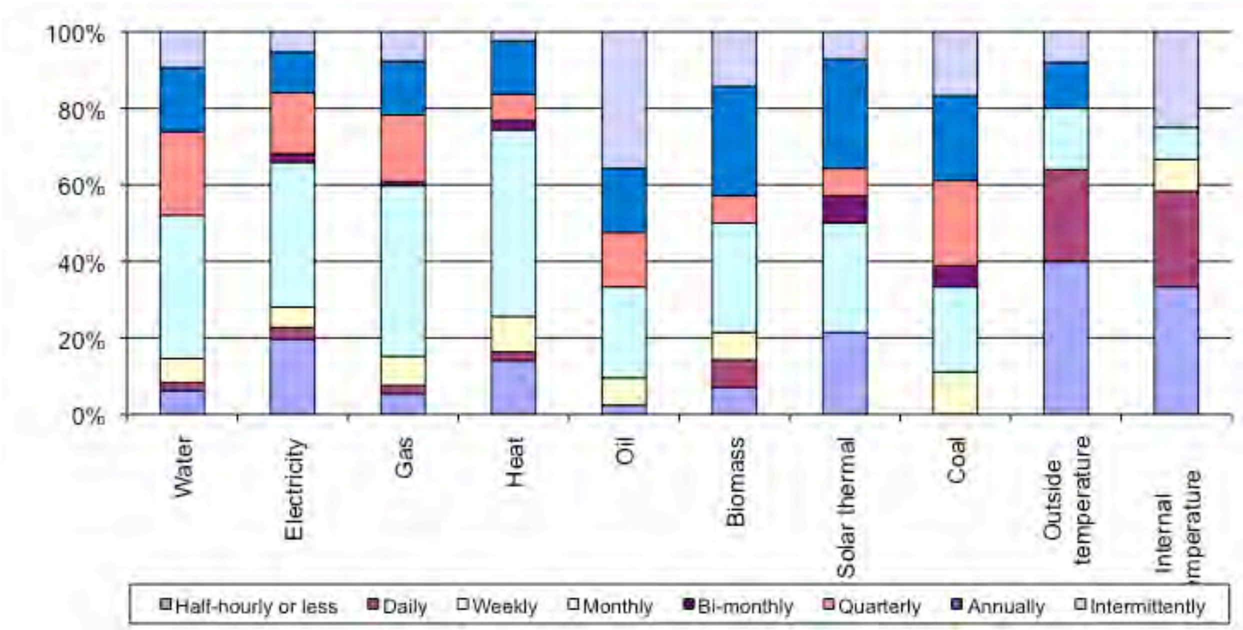

Figure 5. Frequency of water and energy data collection systems per building utility

Figure 5 shows also that data collected in short time series (half-hourly or less) periods is less than 20% for water and energy utilities, except for solar thermal energy production and temperature data (inside and outside). Half-hourly electricity data collection is more frequent than half-hourly water and gas data. For the most important utilities (water, electricity and gas), monthly data collection is the most common metering/monitoring frequency, however, quarterly and annually collected data are also very common.

Figure 6 presents the contrast between the number of municipalities that are collecting data for each utility, with the number of municipalities that are storing data in digital format. Nearly all the local authorities store their building's water and energy consumption data in computer databases, with most of this data is coming from non-electronic format in typically monthly or larger reading periods. This probably requires a resource intensive activity for inputting the water and energy data collected onto a computer database for management or other purposes.

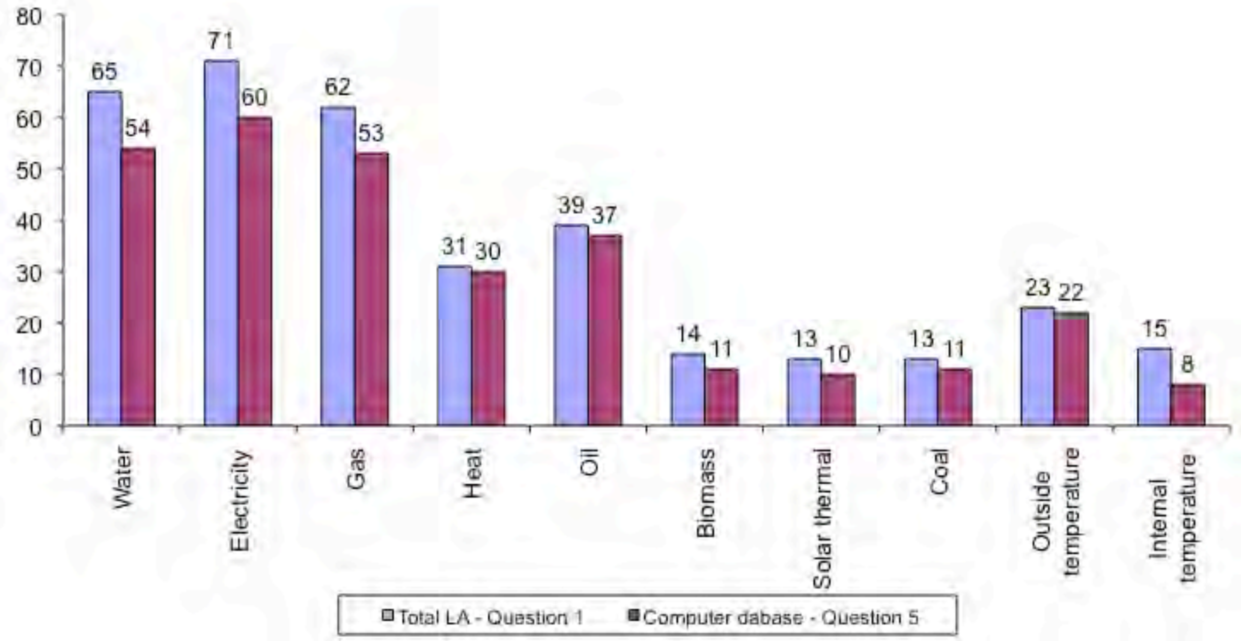

Figure 6. Digital storage of building water and energy data

Applications of collected data

The survey showed that applications of collected data are quite varied. The survey, which allowed Energy managers to select multiple answers from a set of prepared applications and to include additional applications and comments, resulted in a ranking of selected applications as can be seen below (the number of answers on each of the items is in brackets):

- To identify excessively high levels of consumption in normal use (61);
- To verify utility billing data (59)
- To monitor unusually high or low consumption to identify energy wastage (58);
- To measure and verify energy/water savings measures (55);
- To communicate with buildings occupants in order to change behaviour (51);
- To perform benchmarking analysis with similar buildings (47);
- To negotiate with utilities (e.g. in calls for tender for energy supply) (41);
- To measure municipal buildings greenhouse gas emissions (40);
- To communicate with general public, by displaying building performance (36);
- To check for faults affecting consumption permanently (35);
- To prepare dossiers for performance contracting in municipal property (23);
- To ensure that consumption is within the utility contract and avoid penalties (20);
- Not effectively used (11).

Additionally, respondent's comments suggested that data is used to calculate water and energy costs, and several references to calculation of indicators was made: carbon emissions, environmental management, DISPLAY® Campaign (Shilken 2005) and Normalised Performance Indicators (NPI) usually expressed in kWh/m^2 per year. Building certification under the European Directive on energy performance in buildings was also referenced.

|The most important application of water and energy use data is to monitor consumption, identify high levels of consumption, identify wastage and measure and verify water and energy savings measures. In addition

water and energy data is also used to communicate and to promote behaviour change of building occupants. Benchmarking with similar building types is also an important application. The verification of billing information is another important use of water and energy data.

Finally, about 14% (11 out of 76 municipalities) of the local authorities that participated in this survey responded that the water and energy data collected is "Not effectively used". Understanding the reasons why some local do not effectively use building water and energy data in their management is out of the scope of this survey. However, based on discussion with some municipalities, it is likely to be that there are insufficient staff resources to analyse collected water and energy data.

Characterisation of current energy analysis practices

The survey also included open question, aimed at getting more information on the analysis techniques used by energy managers. No new or different techniques from those commonly used were cited. The respondents stated several techniques, the most cited are listed below, the number of citations is in brackets:

- Simple year on year, trend analysis and historical comparisons (5);
- Invoice validation and billing simulation (3);
- Monthly league tables, compare monthly consumptions year on year - current and past (4);
- Analysis using Excel charts (9);
- Graphs showing energy profiles against time (6) - example: Half hourly data for analysis of use profiles for the larger electricity supplies;
- Baseload Analysis (1) - out of hours usage/wastage;
- Regression Analysis with degree days and CUSUM (event detection technique used in energy monitoring and targeting) (5);
- Target based on the pattern/shape of usage - weather dependent, signatures, simple bar charts against historic targets (3);
- Exception reports - examples: variances between the actual usage and the target and would also include calendars and an alarm band width (4);
- Normalised performance indicators (NPI) and performance indicators (PI) – a wide range of indicators was cited, from EMAS performance indicators related to energy and water consumption, to CO_2 emissions from energy calculated using UK's Department for Environment, Food and Rural Affairs (DEFRA) standard methodology, and the conventional consumption per unit floor area (or cost) consumption against local benchmark, MWh/m^3 in month/year (6);
- Benchmarking – once again a wide range of indicators used for benchmarking were cited: internal benchmarks for group of owned buildings, comparison with UK' Department for Education and Skills (DfES) benchmarks for schools, comparisons with similar building types, league table with highest consumers in order, statutory benchmarking, Heat Energy Rating Software, Performance Indicators, Year-on-year comparison using old BVPi 180 indicator for UK's local authority buildings (8);
- DISPLAY® Campaign tool - poster year on year comparison, before and after energy efficiency measures (9);
- Analysis capacities and reports generated by commercially available software packages - such as STARK, TEAM, Energy Controlling System, Erbis, Systems Link Energy Manager, Declic, Energy Monitoring & Controlling Solution, Signum and Enercompta (7);

The survey showed that energy managers use benchmarks (published and internal to the local authority), based on NPI (in kWh/m_2 per year), mostly on an annual basis. Simple visualisation techniques, comparisons between past and current consumption, mostly on a monthly basis, are also used. There are a few references to the use of degree-days, regression and fewer references to CUSUM, a statistical technique used in quality control, also applied in building energy management (Harris 1992). There is only one reference made to the use of half hourly electricity data in the analysis, and this concerned the use of profiles.

There is specific reference to some proprietary software packages used in water and energy monitoring. Microsoft Excel is also used in several local authorities, referred in 9 cases. The DISPLAY® tool was also referred to by 9 respondents.

In the survey, the respondents were asked to select from a list of commonly used energy analysis techniques. The results are presented in Figure 7.

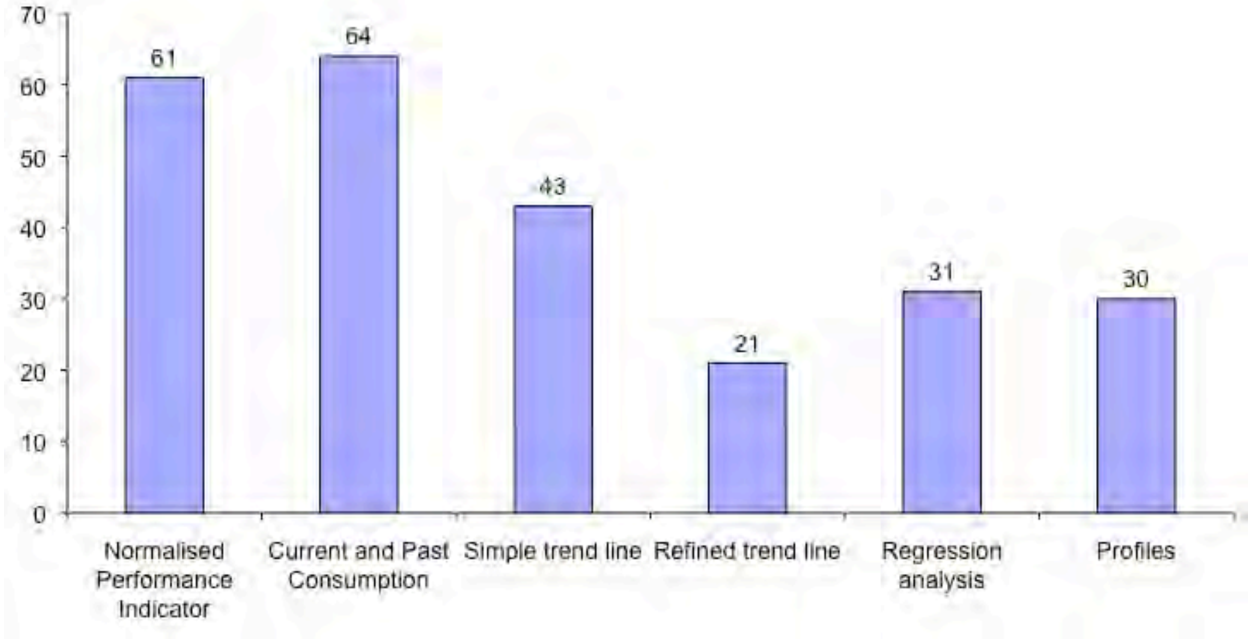

Figure 7. Energy analysis techniques used to analyse water and energy data

The Current and Past Consumption and Normalised Performance Indicator are the most used techniques, followed by the Simple trend line (energy against time). The comparison of current consumption with past consumption is one of the simplest methods of analysing data. However, it does not take into account weather variations, and other variable that changed during the period. Normalised Performance Indicators (NPI), normally expressed in annual energy consumption per building floor area are usually corrected for weather variations. NPI is one of the most common ways of benchmarking building energy performance. More sophisticated techniques such as regression analysis of energy against outside temperature, time series profiles, and refined trend lines are used in less that half of the respondent local authorities. All these techniques have been reviewed in several energy analysis publications, including (Ferreira, 2002) and (Ferreira et al., 2003).

Most local authorities use a standard rating system or benchmark to assess their building's performance. Of the 19 European countries represented in the survey 11 have a national standard rating or published benchmarking system that can be applied to assess performance in municipal buildings, these countries are: Germany, United Kingdom, Netherlands, Czech Republic, France, Austria, Bulgaria, Sweden, Switzerland, Finland and Estonia.

The analysis of data using software packages

The survey showed that 54%, (41 out of 76) local authorities, use a software tool for analysing the collected building water and energy consumption. This percentage is higher in the UK, (81%) compared with the rest of Europe (46%).

The most important input variables for analysis software are electricity, water and gas use data followed by oil, outside temperature and heat consumption. Local authority software tools are also used to analyse coal, biomass, solar thermal and inside temperature. Other input variables indicated by respondents were degree-days, solar photovoltaic and building area.

From the combined analysis of replies to question 10 and question 11 it is possible to conclude that electricity is the most common input variable (98% of local authorities that have software systems) with gas and water both at 88% of local authorities. Therefore most local authorities that invest resources in the development or acquisition of analysis software tools aim to analyse building electricity, gas and water consumption.

The most used municipal building energy management tools are from in-house development, including MS Excel spreadsheets and software packages such as TEAM, System Link Energy Manager, STARK and the

DISPLAY® tool. Most of these software packages were developed and are sold exclusively in the UK. The DISPLAY® tool is available for European local authorities.

European energy managers needs

The final open question was aimed at acquiring information about the needs and expectations of energy managers in terms of hardware and software to manage water and energy consumption in municipal building in Europe.

Concerning metering systems the main requirements requested by energy managers were the following:

- Automatic metering, constant monitoring and real time data;
- Accurate data (not estimated);
- Data management and secure databases;
- System with flexible data import facilities: manual, invoice, electronic data from utilities and automatic metering.

Concerning the water and energy data analysis, including analysis techniques, energy managers stated that they need the following techniques and features:

- Normalised Performance Indicators
- Building classification according to the European Building Directive;
- Benchmarking for costs, energy, water and carbon emissions (local and standard);
- Historical comparisons, current and past consumption;
- Weather adjustment and building energy signature (energy against outside temperature or degree days);
- Constant and weather dependant targets;
- Tariff analysis;
- Billing verification;
- Visualisation of data;
- Electrical parameter reports (low power factor, maximum demand, capacity etc.)
- Exceptions reports, targeting, alarm, warnings, tolerance alarm / error report;
- Budget forecasting;

There were some additional features for monitoring systems that were indicated:

- More automated analysis;
- Easy to use software with user-friendly interface;

The main reporting features suggested by energy managers were the following:

- Suitable report templates and custom reporting;
- Report in units that people understand (money, amount of light bulbs, etc.)

In summary, energy managers requested a more automated, accurate, robust, flexible metering of water and energy consumption data to be used in non-domestic municipal buildings. There is a need for a clear methodology for the overall assessment of building performance, identification of savings/wastages, and benchmarking (internal to the local authority and using approved standards). It was frequently suggested that metering and monitoring could help the implementation of EU Directive on energy performance in buildings.

Conclusions

This was the first comprehensive survey of municipal energy mangers, focused on the collection and analysis of data. It provided information about data collected, the tools, the analysis techniques used, the difficulties and the real needs of municipal energy managers.

It was found that data is being collected typically in monthly periods from paper bills and manual meter readings. However data is being inserted in to digital format and stored in computer databases and about 54% of the respondents use some kind of software tool to analyse data. It is probably more cost-effective to automatically collect data (using electronic bills or automatic metering reading).

Short time series data, in hourly or sub-hourly periods is not yet very frequently used, only about 15% of the municipalities in the study are using this technology. However, the trend is for an increase in the availability of sub-hourly data, and energy managers are calling for near to 'real time' data.

From the survey results, one can say that the most important applications of monitoring systems are the identification of high levels of consumption and wastage and measurement, the verification of savings measures, verification of utility billing data and benchmarking with similar building types. Water and energy data is also used to promote behaviour change of building occupants.

Techniques used by energy managers (including the ones featured in commercial software packages) are not sophisticated enough for dealing with large volumes of data. Energy managers use annual benchmarks (PI and NPI), and simple visualisation techniques, including past and present analysis on a monthly basis. There are a few references to the use of more advanced techniques and weather correction;

Energy managers need an easy to use, straightforward, and as much as possible automatic software tool to analyse building energy data. This is even more relevant when it is expected and increasing penetration of automated metering systems and sub-hourly data in the EU.

In conclusion, there has been very little research on the improvement of energy analysis techniques and software tools in response to energy managers needs. Further research is needed on automating metered data analysis, support for data analysis interpretation and to improve building performance assessment, as part of a certification scheme and energy-auditing programme. New benchmarks using sub-hourly energy and water data can be useful in automating analysis and identifying potential energy saving opportunities. This would contribute to reduce the energy related greenhouse gas emissions in non-domestic buildings across and help the EU move towards meeting its international climate change targets.

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Acknowledgements

The authors would like to thank Ian Turner from Energie-Cités, Jeremy Smith from CEMR and Maryke van Staden from ICLEI-Europe for their support in distributing the survey to European municipalities.

Ferreira, V., Alves, L., Basanez-Unanue, G., Gonzalez, M., Tourlis, N. Pasinetti, R., Siciliano, A. and Kenny, P. (2008) Lessons learned from the implementation of metering and monitoring systems in public buildings in Europe – ENERinTOWN project, In: proceedings of Improving Energy Efficiency in Commercial Building Conference. Frankfurt.

Lessons learned from the implementation of metering and monitoring systems in public buildings in Europe – ENERinTOWN project

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Abstract

In public buildings owned by the municipal, regional or even central administrations, information on energy consumption is usually provided on a monthly, bi-monthly or even on a quarterly basis. Furthermore, typically the recipient of the electricity and gas billing information has no information or training on how to analyse the energy data collected. Therefore it may be difficult to decide whether energy consumption levels and patterns are normal or excessive.

This situation creates an obstacle to the promotion of rational management practices aiming for energy efficiency in existing buildings that need to be addressed – The lack of accurate data and information on energy consumption figures.

In order to tackle this barrier it is being suggested the use of automatic metering and monitoring systems, based on the Internet. Apparently, these systems can be quite cost-effective in helping energy managers and consultants in the identification and quantification of energy efficiency measures, faults and other causes of energy wastages in non-domestic buildings.

Monitoring and control of energy consumption in municipal public buildings over the Internet - ENERinTOWN project, supported by Intelligent Energy Europe programme (Grant Agreement: EIE/05/118/SI2.419653), aims to demonstrate the potential of Internet based metering and monitoring systems for identification of energy savings in European public buildings. Under this project, metering and monitoring systems were installed in 100 public buildings from regional and municipal authorities in Spain, Portugal, Lithuania, Italy, Ireland, Greece, Germany and France.

During the implementation of metering and monitoring systems, under ENERinTOWN project, several technical and non-technical problems arise from the installation and operation of metering and monitoring systems. Some problems were common to all partners, other differ from country to country, and other still differ between municipalities in the same country. The main reasons were the lack of standards for automatic metering technology for energy management (including hardware and software), no harmonisation of procedures in utilities to allow access to existing meters, difficulties in using the Internet for data transmission, and other non-technical problems, such as the number of entities involved in the entire process of installing and operation of the systems.

This paper presents in detail the problems in the installation of metering and monitoring systems found by ENERinTOWN partners, and lessons learned. The objective is to provide knowledge to support the use of automatic metering and monitoring systems in European non-domestic buildings, which can be an important tool to promote energy efficiency and support the expansion of the energy services market in Europe.

Introduction

The new EU Directive on energy services and energy end-use efficiency requires a significant improvement in energy management practices in European public buildings. Public buildings are defined here as buildings owned and/or operated by the municipal, regional and central administrations. The EU Directive on energy services sets a very ambitious, though non-bidding, target for energy efficiency in the public sector in Europe, and improved energy management in public buildings can probably give an important contribution to meet that target.

The major barriers to improve energy management in public buildings are the lack of timely and accurate energy consumption data, and the lack of trained human resources to analyse it take action upon the results.

Usually, building energy management is based on billing data on monthly, bi-monthly or even on quarterly periods. These are very long periods for where waste can occur undetected. Another problem is the fact that often the billing data is based on estimated readings. Here applies the slogan: “If you can’t measure you can’t manage”. Effective building energy monitoring required a continuous monitoring system that provides timely and accurate data in adequate frequency, for example: daily, hourly or sub-hourly.

On the other hand, the recipient of the electricity and gas billing information needs to have information and training on how to analyse the energy data collected, in order to identify and quantify potential energy saving opportunities. This is not usually the case. The presence of a municipal energy manager, trained in energy analysis, is key for promoting a comprehensive energy efficiency strategy in European municipalities. These energy managers should be able to analyse and decide whether energy consumption levels and patterns are normal or excessive, correct faults that lead to energy wastage as fast as possible, identify and implement energy efficiency measures, and measure and verify savings.

In order to overcome both these barriers, and to help energy managers to perform their task it has been suggested the use of automatic metering and monitoring systems based. Apparently, these systems can be quite cost-effective in helping energy managers and consultants in the identification and quantification of energy efficiency measures in non-domestic buildings, (Ferreira et al. 2006) (Ferreira et al. 2007). Furthermore, a recent survey to building energy management practices in European local authorities shows that European energy managers are calling for new technologies and techniques for metering and monitoring energy use in buildings (Ferreira et al. 2008).

The ENERinTOWN project - Monitoring and control of energy consumption in municipal public buildings over the Internet, supported by Intelligent Energy Europe programme (Grant Agreement: EIE/05/118/SI2.419653), aims to demonstrate the potential of Internet based metering and monitoring systems for identification of energy savings in European public buildings. Under this project, metering and monitoring systems were installed in 100 public buildings in seven European countries: Spain, Portugal, Lithuania, Italy, Ireland, Greece, Germany and France. This project is coordinated by the Ente Vasco para la Energia (EVE). More information on ENERinTOWN project can be found on the website: www.enerintown.com. Currently, partners have finished the implementation of the metering and monitoring in the selected buildings, and are undergoing the final stage of the project – implementation of low-cost energy efficiency measures, and measurement of savings.

The objective of this paper is to present the preliminary results that have been achieved so far, but more importantly the partners want to share the lessons learned during the initial stages of the implementation of the project, particularly in what concerns the engagement of municipalities, the technical specification and installation of the electricity and gas monitoring systems. The project partners reckon that this information can be of great importance for other institutions interested in installing monitoring systems, and for the promotion of energy efficiency in public building across Europe.

Engaging municipalities

The opinion on the usefulness of automatic metering and monitoring systems was diverse between municipalities in project partner countries. The perception of the policy makers, officials, and technical staff responsible for energy supply issues was quite important for the success of the project. Nearly all municipalities selected for participation in the project responded positively to the installation of an automatic monitoring metering systems. Typically, two out of the three municipalities contacted accepted participating in project. However, it was found that technical staff more concerned in reducing energy bills in their facilities immediately recognised the value of automatically acquiring energy consumption data in short time series intervals (typically 15 minutes to 30 minutes), and were more committed to the project.

The main reason for the interest of the municipalities was the fact that it was a risk free project. In this project no investment was requirement from the municipalities. And even the more sceptical people, understood the project as an opportunity to assess the potential of automatic metering and monitoring technology in detecting energy saving opportunities in buildings. ENERinTOWN was recognised as a pilot project with very low cost, which could provided a tool for reducing building energy costs, and for communicating environmental–friendly practices with citizens – which are tangible benefits for European municipalities.

Depending on the results of the project, most of the municipalities are keen in maintaining the monitoring systems running, and increasing the number of monitored buildings. This is case of the Provincial Administration of Rome, which considered the project very interesting because they own and manages about 350 buildings in many municipalities of its territory and they are actively working together with institutional and private stakeholders in the promotion RES and RUE activities in its territory. Similarly, EVE, found that this is also the case for the group of Basque municipalities engaged in ENERinTOWN project.

Although there was a clear interest in participating in ENERinTOWN by most of the municipalities contacted, there were also some barriers to the implementation of the project that were immediately identified. Lack of time to follow-up the activities of ENERinTOWN project, and in the implementation of energy efficiency measures. Project partners are to support municipalities in all the stages of the process, by providing training and by setting up a bureau service for the analysis of collected data. At the operational level, some technical staff were not that interest in the project, and often the reason was the fact that responsibilities in building energy management were not clearly assigned. In fact, the lack of ownership of energy issues inside municipalities was the main barrier found in engaging the municipalities. This was address by providing training, and by engaging managers and technical staff in building energy management. Municipalities were also concerned about the costs that proposed energy efficiency measures could have. If the cost were to be high they would not have the financial capacity to implement them. It was decided that monitoring systems would aim to identify no-cost and low cost measures. The savings introduced by these initial measures could then be used to finance medium to high-cost ones.

In summary, municipalities contacted recognised the opportunity offered by automatic metering and monitoring systems. ENERinTOWN project was seen as a pilot project that would help to assess the cost-effectiveness for monitoring systems in detecting energy cost savings in municipal buildings. The municipal staff, and energy managers, more experienced in energy issues, recognised immediately the activities in which the system can be used to help them reducing energy costs. Others, more sceptical about the use of monitored data, were concerned about the staff time and investment required for energy management and for reducing building energy bills. The support provided by project partners, by providing training and technical assistance in all steps of the implementation of the system, analysis of data, reporting and verification of savings. There is a the real possibility that municipalities engaged in the project will continue to run the system and even increase the number of monitored buildings. All the project partners are interested in to develop further and continue to offer this service to municipalities.

Number of municipalities engaged in ENERinTOWN

Partner	Country	Number of municipal energy managers involved
EVE	Spain	4
INEGA	Spain	4
LDK	Greece	2
TEA	Ireland	4
IST	Portugal	2
AREAL	Portugal	3
ADEME	France	6
LEI	Lithuania	4
AI	Italy	2

In total the project partners manage to engage 29 municipalities to participate in ENERinTOWN project. These municipalities selected buildings to be monitored. The total number of building monitored under ENERinTOWN project is 100 buildings, distributed by 7 European countries.

Distribution of selected buildings per partner and per country

Partner	Country	Number of buildings
EVE	Spain	12
INEGA	Spain	12
LDK	Greece	12
TEA	Ireland	12
IST	Portugal	4
AREAL	Portugal	12
ADEME	France	12
LEI	Lithuania	12
AI	Italy	12

Metering and Monitoring Solutions

During the implementation of metering and monitoring systems, under ENERinTOWN project, several technical and non-technical problems arise from the installation and operation of electricity and gas metering and monitoring systems. Some problems were common to all partners, other differs from country to country, and other still differ between municipalities in the same country. The main reasons were the lack of standards for automatic metering technology for energy management (including hardware and software), no harmonisation of procedures in utilities to allow access to existing meters, difficulties in using the Internet for data transmission, and other non-technical problems, such as the number of entities involved in the entire process of installing and operation of the systems.

Partners were free to select the best technological solution that they could find in their countries. The next sections present information on the barriers, solutions, lessons learned and final monitoring solution implemented in each partner country.

France

ADEME opted for tendering the installation of metering systems and for the development of an open-source software tool. This open source software package includes basic energy analysis functions, such as reading load curves, and benchmarking between similar building types.

Germany

ZREU in Germany have been involved in a successful projects using an energy management system for distant reading of electricity, heat, gas and water meters, featuring data analysis and automated generation of energy consumption reports. The Resource saving project in the city of Geislingen was the basis for the development of the ENERinTOWN project. This project was developed for 80 facilities in the City of Geislingen.

The German energy management system is an Internet based electronic software tool developed by an associate company. This company was in charge of all the installation of the hardware and software. The software tool automatically collects data from heat, electricity and water meters. It allows for the continuous monitoring of resource consumption, the calculation of benchmarks and the automated generation of energy consumption reports (monthly and annual).

The no cost and low cost measures identified in the city of Geislingen during the first two years reduced by 15% energy costs, and were about 340,000€. In the years before the project started the annual cost for heating, electricity, water/waste water and waste collection amounted to 1,700,000 €, (Konradl, J. et al. 2007).

Greece

During the installation of the metering and monitoring system in Greek municipal buildings, LDK found some technical, market and administrative barriers.

The technical barriers were on the fact that not all the buildings are connected to the natural gas grid. The project had a clear objective of monitoring gas, and therefore this limited the selection of municipal buildings for ENERinTOWN project. It was necessary to invove the regional gas utility in order to acquire information on the type of connection, level of completion, type of equipment used as well as arrangements that have to do with the operation of the gas network (i.e. access to sites where gas meters are physically located).

The physical instalation of the harware in some buildings required extensive wiring the interior and exterior of the building, which increased the cost and time spend on the installation of the systems. Alteration of the installations, in the light that the new arrangements to integrate the metering system, had to be discussed carefully with building managers. Some were against any alterations, because they were afraid of installed equipment interfering with the continuity and quality of service of the facilities.

Available electricity meters for low voltage, in local market did not include communication capacitibilities, and power factor measurements. This is due to the nature of existing tariffs for this type of electricity supply. Harmonisation of communication protocols between meters, dataloggers and software packages was either impossible or otherwise expensive. The technology providers that have turn-key metering and monitoring systems are not represented in Greece.

There were also some administrative barriers in the implementation of the project. The October 2006 elections, and the change of Council officials resulted in a significant and unexpected delay in the project implementation.

The final technical solution follows a centralised philosophy in order to optimise cost over independence of operation. Metering electricity and gas data are stored in the electricity meter, registers are then transmitted to a local PC, and then to a central internet server located. Once all sets of data are accumulated into the server, a data transfer application runs between it and the data warehouse of the energy management suite via a single communication channel. The advantage of this option is minimisation of costs for data-transfer as only one proprietary software will be purchased. Nevertheless, this centralised operation has a certain degree of risk because once the single communication channel fails, communication of all the metering points can be compromised.

Ireland

In Ireland the approach was to use many different solutions in order to have a detailed understanding of the possibilities going forward. The approach was to use data loggers at the point of energy use and transmit via the most cost effective or available solution. For the 12 buildings the following methods have been employed:

- GSM for remote sites (4 sites);
- Landlines for sites not connected to the internet (3 sites);
- VPN connection through the internet (2 sites);
- Server to logger via IP, automatic email from server to other server (3 sites).

We have encountered several problems:

- It was decided to use local technical staff to ensure future knowledge of the systems and to increase their technical understanding. This led to many many problems due to lack of skills.
- Supplier of equipment had never worked with non-experts;
- Data communication via firewalls;
- Some IT staff did not consider this project as core work and dragged their feet as much as possible slowing the connection process;
- New untested logger with integral email function was tried, getting the correct electronic interface with the IT systems was a challenge.

The technical solution to be employed in the future consists of the use a GSM based pre assembled unit that has all the facilities connected through it. This would mean a slightly higher equipment cost, but a lower overall labour cost. It would also ensure that the installation of energy monitoring is seen as a positive step rather than a hassle. After the data is collected in the central server, an Internet based proprietary software package will be used for data analysis and reporting.

Italy

For metering electricity consumption the choice was to use digital counter with current transformer. A current transformer is a type of "instrument transformer" that is designed to provide a current in its secondary, which is accurately proportional to the current flowing in its primary. In this way it was possible to measure high intensity current.

To measure the thermal energy consumption of the buildings the main problems was that gas meters are generally too old and it is not possible to change them or use pulse transmitters. So it was decided to monitor the thermal energy given by the plant and to use the real thermal energy efficiency to find gas consumption.

Another problem is connected at the Internet transmission systems. The Internet connections are too far from the thermal and electric counters. For some buildings digging works were necessary, and this increase the intrusion of the installation of the systems, and the costs. It was decided that GSM communication was the most suitable for transmitting data from the meters to the central data server. The analysis software chosen is the Energy Brain free distributed with the electricity meters that were selected, but It can manage thermal energy data.

Lithuania

For data collection Electricity and Heat/Gas meters are connected trough the M-Bus interface. Data is acquired by the software package Connecty EtherMeter device, which collects the readings from all the meters and makes them available trough the LAN (local area network). Data monitoring is performed using a standard Web browser. Every user is authorized. Permissions are personalised for each user and device. User can access only to devices and their properties to which he has appropriate permissions.

Portugal

IST and AREAL the two partners institutions of the project in Portugal. IST installed monitoring systems in four facilities in the Lisbon Metropolitan Area – Almada and Oeiras municipalities. AREAL installed monitoring systems in 12 buildings in six municipalities in the Algarve region.

Although all the selected buildings have Internet access, the municipalities IT departments were not very keen in allowing a direct connection to the building LAN and router. Another technical difficulty concerned the large distances between meters, and between meters and Internet access points. In some building it would be necessary extensive and costly cabling works to connect the meters and to access Internet. So, one of main challenges was to finding a cost-effective technical solution that solved both problems: limited Internet access for data transmission and the intrusive cabling needed for connecting the metering equipments. Another difficulty was the fact that some gas meters did not have pulse outputs, and the gas supplier company was not willing to replacement gas meters. Additionally, the partners found that some buildings did not have gas meters, this happened in Algarve region, where buildings use propane gas, stored in large tanks. The cost of installing new meters was extremely high, so the partners had to abandoned this option, and in alternative there will be a weekly manual reading of gas meters without pulse output and of the level of gas tanks.

IST and AREAL decided to prepare a joint tender, in order to increase the negotiation capacity. Five solutions were received from 4 companies. The chosen technical solution of the metering and monitoring system consists in the installation of electricity meters with extra data channel and data logger, a pulse reader and wireless/radio transmitter of gas use pulses to the electricity meter. No cable connection between electricity and gas meter is necessary. The electricity meter built-in GSM modem transmits data to a server database. The analysis of data is done through Internet based energy management software. The web monitoring system is available 24-hours a day on the Internet. The proprietary energy management solution is commercially developed by a Portuguese company, and is available worldwide.

Spain

In Galicia region, INEGA installed monitoring systems in 12 facilities in 5 Municipalities (Santiago de Compostela, Maceda, Meaño, Monterroso and Laxe)

For monitoring electricity use new electricity meters with extra channel data logging capability and LAN modem were bought. These 3-phase low voltage meters were limited to 80 A current. The objective was to connect the pulse output of the gas meters to the electricity meter and store it in data logger extra channel. However, in some buildings there was no natural gas use, only oil. So INEGA had to buy and install oil meters.

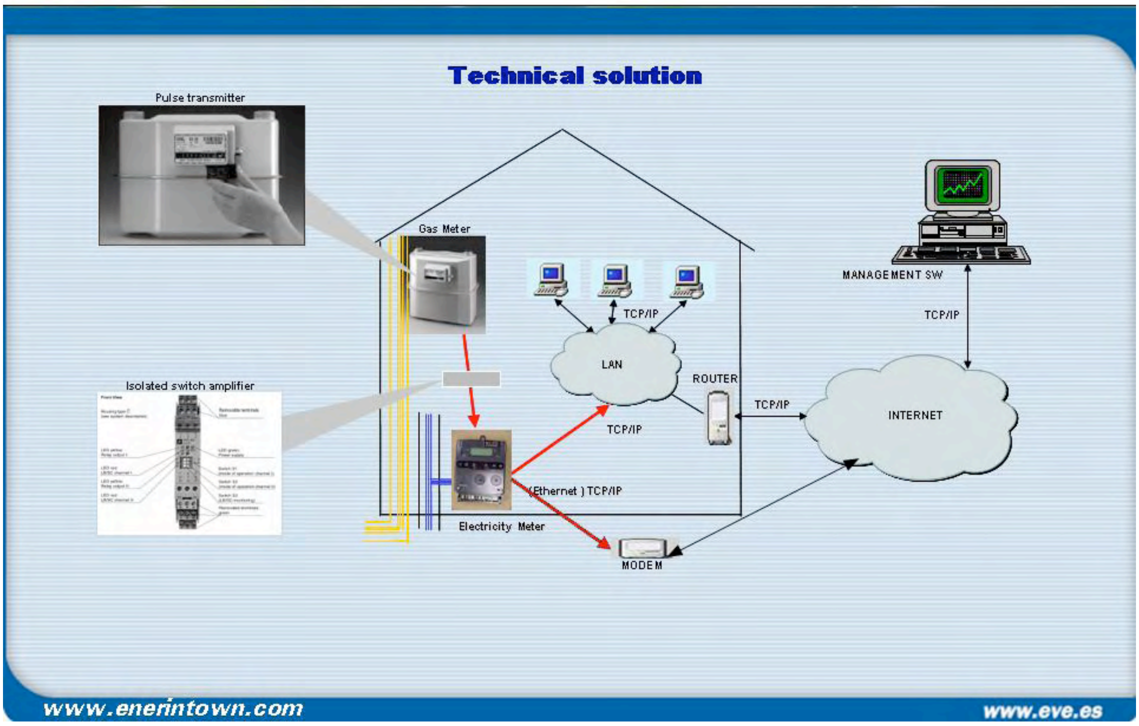
There were some time consuming problems, concerning internal administrative steps to get the necessary authorisations for installing the meters and for connecting them to local Internet routers, and for transmitting data from meters using the existing infrastructure. Another problem were the large distances between meters, and between meters and Internet access points. The required wiring was quite expensive and intrusive.

INEGA's in house developed data acquisition software - MEDCOM PLUS, only had the capability to connect with the meters by modem, so software had to be modified to allow connection directly through LAN network. The in house data analysis software – SIGEST, was only prepared for electricity data analysis, and therefore extra models for gas and oil consumption analysis had to be included.

In the Basque country, EVE selected the technical metering and data transmission solutions adapted to the buildings. Concerning communications over the Internet, the use of the municipalities' internal networks raises a series of problems of accessibility in the internal LAN but not all IT managers were willing to assume. It was therefore proposed that as a definitive solution to these problems, would be a specific VPN (Virtual Private Network) adopted for the actions of monitoring energy consumption in the buildings.

In the case of the Basque country, the involvement/coordination of different agents in the project (meter manufacturer, software company for data transmission, utility, local authorities, companies in charge of the communications systems (Internet), was found to be very time consuming. The solution would be o have a single agent responsible for providing the monitoring service or technical solution for the entire system, ensuring continuous data transmission from the meters to the control centre. EVE technical solution is presented in the next figure:

Metering and monitoring technical solution implemented in the Basque country



A new electricity meter was installed in all the buildings. This new electronic meter has a data logger with and extra channel for storing gas pulses, and landline and TPC/IP modem. Pulse transmitters were installed in gas meters, and isolated switch amplifiers have been placed between the gas meter and the electricity meter. Gas meters with no pulse output have been replaced by the utility. Data is transmitted through the Internet to the database server. An Internet based software is used to analyse metered data, trigger excessive consumption alarms and for automatically reporting and benchmarking.

Conclusions

Generally speaking, municipalities understand the potential of automatic metering and monitoring systems. However, more information on the benefits of automatic metering and monitoring is required, particularly more information on the technologies available for metering and communication, quantification of savings achieved in different building types, guidelines for data analysis and identification of faults, energy wastages events and opportunities to reduce energy use and energy costs.

During the implementation of the metering and monitoring system project partners experienced a mix of barriers and successes that is important to share. The major issues that needed to be addressed were: integration of systems and communications (between meters, and between meters and databases). The metering and monitoring technology exists on most of the markets in the target countries, at different levels of development. In most cases the specifications did not match exactly those of the project. The project aimed at the use the Internet for communication between meters and database and between the database and the energy managers. The later was found to be easy to do, however the transmission of data from the meter trough the Internet to the database was in some cases impossible. Alternatives had to be sought.

There are various technologies for carrying out the actions of metering electricity and gas use, storing data, and for sending the information to the management centres – databases and to analyse data.

Given the wide range of types of buildings to be monitored, the communication solutions have to be flexible, and several options have to be available (for example TCP/IP, Wi-Fi, landline, GSM, or radio) in order to allow the integration of different systems. Experienced technology providers are the key for effective delivery of an automated metering and monitoring system.

Engaging all the stakeholders inside the organisation, and make them aware that monitoring systems do not save energy automatically. Automatic metering and monitoring systems should be seen as a tool to be used by trained people – energy managers. It can be helpful in the identification and quantification of energy cost saving measures in buildings. It can also be applied to measure and verify effective savings achieved after actions have been implemented.

ENERinTOWN is an on-going project, results and case studies on the 100 buildings monitored will be published in late 2008. In the meantime, more updates and deliverables are available at www.enerintown.com.

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"Low hanging fruits" or cost-effective energy and water savings using intelligent metering and monitoring systems?

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Keywords

Energy, water, metering, monitoring, local authority, buildings, Directive on end-use efficiency and energy services

Abstract

The paper presents Leicester's approach to identifying energy and water savings in local authority buildings (schools, libraries, leisure centres, swimming pools, administration offices, warden assisted accommodation, maintenance depots). Traditionally Leicester City Council collected and analysed monthly and quarterly utility billing data to identify energy and water saving opportunities. More recently, it has been gathering electricity, gas and water consumption data on a half hourly basis using a proprietary system which combines information technology and a proprietary software package. Energy and water consumption for nearly 300 local authority buildings is metered and monitored continuously. Electricity, gas and water meter readings are taken at half hourly intervals, and after being collected in a central workstation data is automatically checked for errors. The data is then analysed by the energy manager using the software's built-in analysis techniques, leading to the detection of potential energy and water savings. The initial savings are usually caused by incorrect operational management and maintenance procedures – sometimes described as "low hanging fruits". Once these operational issues have been solved, the analysis helps maintain effective energy and

water management of the buildings. This paper presents the actual costs and savings produced, and examples of the "low hanging fruits" picked up by the new metering and monitoring system.

Introduction

In recent years there have been great advances in technology to measure, acquire and store large quantities of short- time series (usually in half-hourly and quarter-hourly intervals) energy and water consumption data. Technology is becoming less expensive and the need for more accurate billing in the new liberalised energy markets is driving the increasing availability of such 'smart' metering. The short-time series data for a large number of buildings and sites is available to be analysed using different data analysis software techniques to manage energy and water consumption in buildings.

The recently approved Directive on End-Use Efficiency and Energy Services will be another important driver for the development of new metering and monitoring practices for improved energy efficiency in the European Union. Article 13 of the Directive requires Member States to ensure that meters and systems measure the actual energy consumption, both accurately and frequently. Energy users should have access to good quality and frequent billing information. This is expected to have an impact in delivering energy savings. However, there are other potential applications for intelligent metering, particular for grid management and demand side management. Continuous monitoring and performance assessment can quantify and verify energy and water usage following corrective actions or the implementation of efficiency measures. This can be accurately carried out using short time series data together with effective analysis techniques. Analysis on the use of short-time series electricity data and innovative analysis techniques have already been tested and documented for UK office buildings (Ferreira et al. 2003) and UK secondary schools (Stuart et al. 2007). It has also been suggested in (Ferreira et al. 2006) that the use of intelligent metering and monitoring can be used to increase the cost-effectiveness of conventional energy audits. The experience of the Leicester energy agency suggests that occasional or even regular energy performance assessments or energy audits are not the only tool for municipal building energy management. They employ a first resource approach for the identification of savings and evaluation of energy and water efficiency and renewable energy projects: the collection and analysis of half hourly electricity, gas and water data, using an intelligent energy and water metering and monitoring system in their municipal buildings.

Leicester intelligent metering and monitoring system

Leicester City Council collects utility data using a proprietary system which combines information technology and a proprietary software package, which is commercially available under the label "Automatic Monitoring and Targeting (aM&T) system. The aspect of aM&T, which differentiates it from more traditional M&T is the capacity to profile energy and water use and automatically highlight variances from set patterns or expected outputs. The half-hour analysis is critical to enable variances to be acted upon immediately.

In Leicester's intelligent metering and monitoring electricity, gas and water meter readings are taken at half hourly intervals and recorded onto a data logger locally. Data is also collected from district heating heat meters and from automatic weather stations. Each day the 48 daily readings from each (electricity, water and gas) meter are transmitted by low power radio to one of seven main receivers, similarly to the system presented in (DETR 1996). The main receivers then forward the data on to a central receiver located in the energy office where it is stored and analysed. It is possible to test the relationship between energy use and weather and/or occupancy. The proprietary software is used to plot it as charts at various resolutions; it also provides regression analysis and generates alarms when consumption falls outside predetermined levels. In summary the proprietary software's main features are:

- Graphical display of data (including profiling with target setting);
- Regression analysis with degree-days (assess weather related consumption);
- Cumulative sum of the differences from an existing pattern of consumption;
- Year on year comparison;
- Reporting functions, including exception reporting.

Currently the Leicester City Council system collects and performs analysis on gas, electricity and water data for about 280 buildings, including:

- Schools;
- Libraries;

- Leisure centres/Swimming pools;
- Administration offices;
- Elderly persons homes;
- Warden assisted accommodation;
- Maintenance depots.

Costs and savings

The cost to set up the energy and water metering and monitoring system is of the order of 3,750 Euro to 4,500 Euro per building. In the current contractual arrangement with the aM&T technology providers, about 60% of the cost to set up metering and monitoring is for the hardware (new metering equipment), about 25% is for connecting the new and existing meters to the monitoring system and 15% is the labour costs of the installation.

Leicester intelligent metering and monitoring system started to be installed in 2002, when a pilot demonstration of aM&T of 10 buildings was implemented. Until now the total investment in the system, which includes the 280 buildings was about 1,155,000 Euro (approximately over the last 5 years). The annual maintenance costs, which include all the cost of keeping the system running, from software updates to replacement of batteries in data loggers is about 52.500 Euro per year. Data transmission from the seven main receivers to the central computer, performed on a daily basis, costs about 750 Euro per year.

So far, estimated savings on energy and water, the so called "low hanging fruits", are in the order of 225,000 Euro per year (2006 figures), and this figure is increasing rapidly as more buildings are being added to the a M&T system. When no more of new buildings are added to the system, and after all the low hanging fruits picked up, the annual savings produced by the system are expected to be reduced. The system will be exclusively performing monitoring and targeting, i.e. detecting uncommon consumption patterns.

Typical "Low hanging fruits" identified

The intelligent metering system assists in the building operational management, but it also can help in diagnosing consumption patterns that might be indicative of excessive energy and water consumption. It allows potential savings to be accurately quantified. Frequently, energy and water cost savings can be attained by simple no-cost, and low cost corrective measures, these are what can be labelled as "low hanging fruits". These savings would probably be undetected if it was not for the continuous metering and monitoring system, and they even could pass unnoticed in a short walk around survey to the building, or at least would not be fully explored. Most of these savings were not physically visible, as they were not noticed by the building manager and building occupants. These were only detected because of the analysis of high resolution data, which pinpointed unusual patterns that were then proved to be caused by water or energy wastage. Leicester Energy Agency (Leicester City Council) provides, remotely, technical and analytical support to the building managers along the entire process of detecting and quantifying savings.

The first, most common and important low hanging fruit ready to be picked by the energy manager in charge of the metering system are water savings. So far water monitoring is yielding the best results in terms of cost savings and when comparing with electricity and gas. In Leicester buildings, water savings represent about 60% of the total savings. This is due to the relative straightforward identification and elimination of water wastage. After wastage is identified by the energy manager, there are only a few areas to eventually investigate further on site in order to complete the wastage diagnosis and correction. Typical savings are usually achieved by repairing water leaks in valves, toilets, kitchens, tanks and in plant rooms.

The second most important low hanging fruit that would remain undetected if it were not for the half hourly metering and monitoring concern gas wastage representing 25% of the total savings identified. The energy manager in Leicester Energy Efficiency Centre conducts the analysis to the half-hourly gas data comparing consumption in the occupied to the out-of-hours periods, and calculating the building energy degree-day signature (Harris 1992), i.e. the regression analysis between gas consumption and degree-days. This relationship is then used as a target to compare against the actual consumption. Overnight gas consumption and heating control problems are the typical anomalies identified and easily corrected. Poor maintenance of the boilers and heating systems are also detected with the metering and monitoring system. The system is also used for benchmarking purposes.

Electricity wastage is far more difficult to identify. Although the intelligent metering and monitoring system enables the analysing of high detailed data in half-hourly periods, in most of the building there is only one electricity meter installed and therefore the energy manager does not have the possibility to analyse the performance of individual equipment. Therefore when an unusual electricity consumption pattern is detected, the identification of the cause is not straightforward, and in some cases requires an on site comprehensive inspection. Nevertheless there have been simple no-cost, and low cost corrective measures implemented in Leicester municipal buildings to eliminate electricity wastage, which represents about 15% of the total cost savings implemented.

Although Leicester's intelligent metering and monitoring system is running smoothly, needs has been identified to improve the methodology for energy and water saving detection, particularly for electricity. The process is still very resource intensive in terms of time the energy manager spends in data cleaning and data analysis. A more automated system is required, leaving more time for the energy manager to detect energy savings and to report on them, as well as to promote action by engaging building managers and occupants and provide technical support to the implementation of energy and water efficiency measures.

Examples

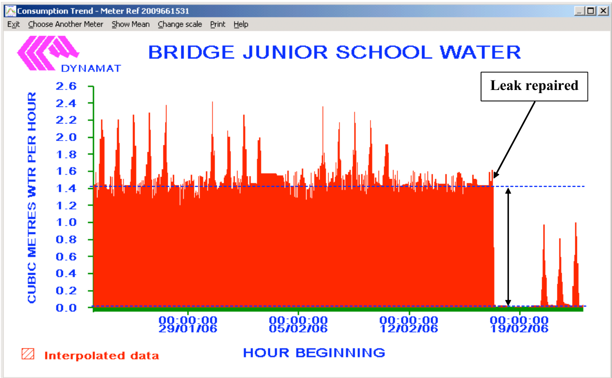

Figure 1. Detection and elimination of water leak

In Bridge Junior school it was possible to detect and eliminate a water leak leading to the saving 9,638 cubic metres and 23,130 Euro per year. This water leak was found in buried pipe between the meter and the main valve of the building. Water had been leaking to the soil for an undetermined period of time and it would be unnoticed if it was not for the installation of the aM&T system that detected an unusual base load consumption, as presented in the figure 1.

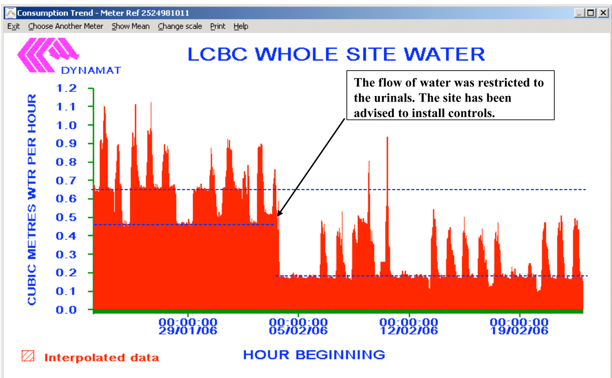

Figure 2. Detection and partial elimination of water flushing control in urinals

In Leicester Creative Business Centre, a recently refurbished building, the intelligent metering system helped the energy manager detect 4,467 cubic metres and 10,722 Euro per year of potential water saving. The waste was being caused by the lack of urinals controls, and therefore the water tank would fill in and flush the water into the urinals continuously. None of the building occupants had detected this situation. The immediate solution was to reduce the flow of water in the restricting valve. This no-cost action reduced 2,715 cubic metres and 6,516 Euro per year, as presented in figure 2. In the meantime urinal controls will be installed in the building, and the resisting base load water use will be eliminated.

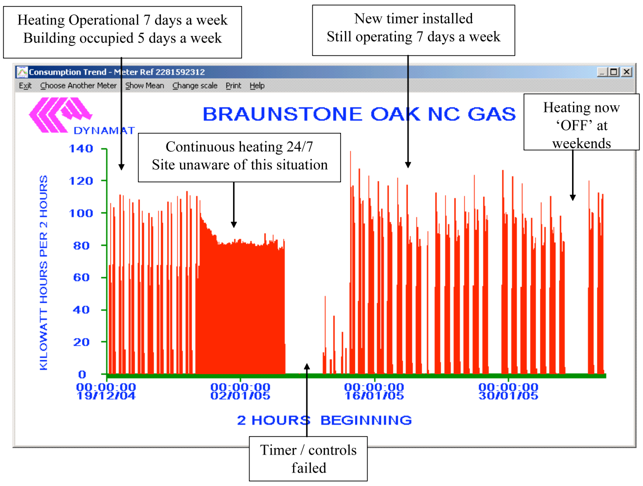

Figure 3. Diagnosing and elimination of space heating timer control problems.

In Braunstone Neighbourhood Centre the heating controls failed in the on position, and this caused the heating to be on 24 hours 7 days a week. However the building is only occupied about 10 hours from Monday to Friday. The energy manager contacted the building occupants to communicate the problem. However before they have the chance to investigate in detail what was happening the the timer controls failed completely and the building had no heating for several days. After these events, a new timer was installed, initially heating was still on 7 days a week, but then it was reset to shut the heating over weekends. Figure 3 present an overview of the events using the aM&T system.

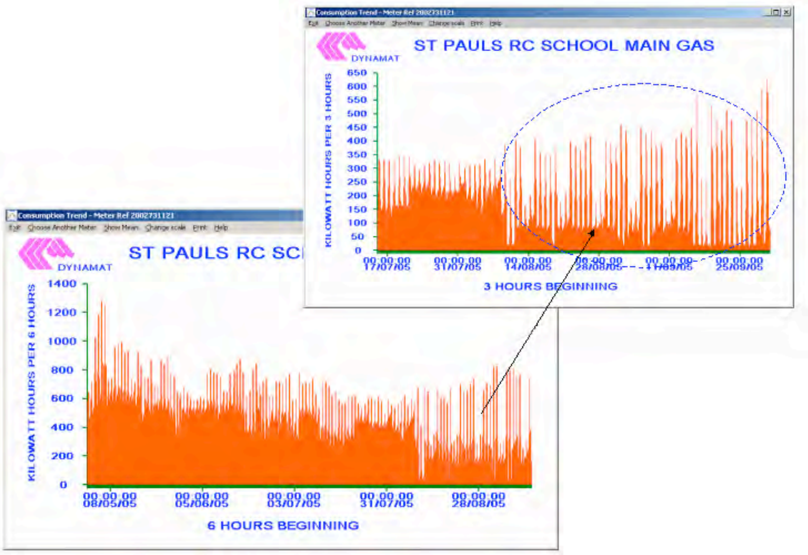

Figure 4. Detection and elimination of gas wastage; change in control set point saved 740,000kWh and 22,200Euros per year.

In St Pauls School gas consumption was reduced by 740,000kWh per year, by resetting the control set point temperature. This originated about 22,200 Euros of gas savings per year. In figure 4 it is clearly to see the high and variable consumption that was indicative of potential energy wastage. This caught the attention of energy manager who then visit the building and reset the control set point temperature.

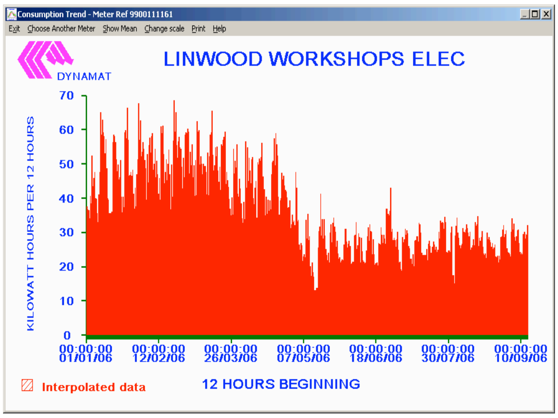

Figure 5. Measurement of electricity savings through the installation of occupancy lighting controls in corridors and bathrooms.

In figure 5 presents documents the saving achieved by installing occupancy lighting controls in corridors and bathrooms at Linwood Workshops in Leicester.

Conclusions

The intelligent metering and monitoring system is cost-effective (including investment and running costs) even when most of the energy and water savings achieved though simple no-cost or low cost measures - “low hanging fruits”. Once these “low hanging fruits” have been picked, the effective (annual) savings might be reduced. However the ongoing monitoring of the buildings will ensure buildings are continuously operating efficiently, it will help to quantify the savings from any energy efficiency improvement measure and to identify further energy saving opportunities.

Intelligent metering and monitoring systems based on short time series metered data and adequate energy analysis techniques can clearly contribute to the implementation of Directive on End-Use Efficiency and Energy Services, and for Member States energy efficiency and carbon emission reduction targets. The results of the study of Leicester’s municipal building intelligent metering and monitoring systems indicates that there is probably a significant potential for replication in other European municipalities.

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building performance congress

Intelligent energy and water performance assessment in municipal buildings

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Abstract

Energy audits are an essential aspect of the promotion of energy efficiency in non domestic buildings and businesses. Energy auditing activity is becoming increasingly important, with the implementation of new instruments for promoting energy efficiency in buildings, such as the Directive on Energy Performance in Buildings and the proposal for a Directive on End-Use Efficiency and Energy Services. Across Europe, there are several terms and definitions of what an energy audit is, for instance in the UK this energy audit is referred as energy survey. In this paper we use the term energy audit based on the definition used in the proposal for a Directive in End-Use Efficiency and Energy Services.

The paper presents a discussion of the relevant issues from published literature on energy auditing and on the evaluation of energy efficiency programmes. The focus is on the quality of the energy audit results and its cost with the overall success of the auditing activity measured in terms of effective energy savings or carbon emission reductions.

From experience gained in the field and from the review of published literature, it was found that there are still significant opportunities for innovation in the field of energy audits, in particular opportunities for improvements in the cost-effectiveness and quality of energy audits. This might be attainable by the development of new integrated methodologies, tools and techniques to reduce the time needed to identify energy saving measures, related to audit costs or other transactional costs such as time the client/business spends on collecting energy and other relevant data.

The paper presents a new approach for assessing energy and water performance assessment in buildings based on the use of metered (half-hourly) data collected by the monitoring and targeting system using automatic meter reading systems, energy analysis techniques and communication technologies. Results from the energy and water monitoring and targeting system used in Leicester City Council buildings are presented and assessed in terms of its cost-effectiveness.

The application of readily available metered data and advanced energy analysis techniques can be an important tool for improving the cost-effectiveness of the activities being pursued by Member States for the implementation of the Directive on Energy Performance in Buildings and the future Directive on End-Use Efficiency and Energy Services, and of course for achieving the international carbon emission reduction targets

Background

Terms and definitions - Energy audit

Energy audits or energy surveys are generally the first step in assessing energy performance and identifying energy saving opportunities in buildings. There is no unique definition of what an energy audit or an energy survey is. The definition and understanding of what energy audits involve varies between countries. The definition of energy survey, energy assessment and energy audit, are often interchanged on translation. For example, what in mainland Europe is generally referred to as an energy audit, is understood in the UK as an energy survey. In the UK the term energy audit is used when referring to a simple study that just determines the quantity and cost of each energy input to the building, as in (CIBSE 1991). However, there are other authors in the UK refer to the energy audit process as involving the assessment of the energy management structure within an organisation in relation to an energy matrix tool, (Harris 1992).

Hereon, and in order to contribute to the harmonisation of terms and definitions, we will use the term energy audits and the definition included in the proposal for a Directive in Energy End-Use Efficiency and Energy Services, which states that an energy audit is a systematic procedure that obtains adequate knowledge of the existing energy consumption profile of the building site, industrial operation, etc.; identifies and quantifies cost-effective energy savings opportunities; and reports the findings.

Recent research has been focusing on several issues concerning the usefulness, cost-effectiveness and quality of commercially available energy audits and energy efficiency programmes that include subsidised or even free audits. The main findings of published literature on energy auditing are presented in the following sections.

Energy auditing programmes

There is some energy auditing activity in most EU countries. This began following the oil crisis in the 70's and early 80's, reduced during the period of low oil prices in the 90's and is now enjoying a resurgence with action to reduce energy related carbon dioxide emissions.

The support of energy auditing activities by energy efficiency and energy auditing programmes has been a common practice in several EU countries. These programmes have been developed in order to support the implementation of a national energy policy and they are usually focused on a particular sector and include energy auditing activities as an element of the programme. However, and despite all this activity, little attention has been given to monitoring and evaluating energy auditing activity and assuring that they offer energy audits at a minimum cost and maximum quality. In particular very little information was found on the objective and accurate evaluation of cost-benefit of energy efficiency, energy auditing programmes or other initiatives that are based on energy auditing activities. In light of the restructuring of the European energy markets, and in particular with the future introduction of a new instrument on the demand side - the Directive on end-use efficiency and energy service, the study of the cost-effectiveness of energy auditing programmes it is now very timely. The bibliographic references found on the evaluation of energy auditing programmes (in the English language) are presented and briefly discussed in the following section.

One of the first papers found is (Jordal-Jorgensen 1995), who presents the results of the Danish Heating-Audit Scheme (HA), an energy auditing programme that has been operating since the early 80’s and that currently funds about 5000 energy audits per year. Although this study is on domestic buildings, is relevant, because of the methodology used in the analysis of the economy of energy audits. There are 2 perspectives to which energy audits cost-effectiveness and investment in energy efficiency has to be analysed (in the form of present value of the measures carried out, i.e. investments in energy efficiency):

Private economy perspective, shows the economic result of the heating audit to the private households;

Socio-economic perspective, shows the result of the HA scheme to the society as a whole, calculated in monetary terms.

The study included a survey to householders, and it was found that 25% of the total energy efficiency measures were carried out, 8% had been partially carried out and 47% were rejected. Interestingly 79% of the respondents replied that the energy saving measures would have been implemented even if the energy audit had not been carried out. The authors considered that half of this replies were truthful and accounted for 40% of free-riders in order to calculate the present value of investments in energy efficiency. They concluded that the:

The HA Scheme is relative expensive (both from the private economic and socio-economic perspective), however there are valuable side-effects that are not considered in the analysis such as: improved indoor-climate, employment creation and added information when buying a house.

Cost-efficiency of the scheme could be improved if only the most important energy saving measure were included (insulation, automatic boiler controls, etc.) and limit audits to buildings with larger potential for energy savings.

(Larsen 1999) assessed various energy auditing schemes in Denmark not only aimed at the domestic sector but also at industry. The aim was to know “How much energy was saved as a result of the energy audit, and what was the result from an economic viewpoint?”. Ibid. continues and analyses the response by energy authorities using 3 different decision-making theories in order to explain why loss-making schemes have been upheld or expanded.

For the analysis a model of audit evaluation and a cost-efficiency analysis was used. Consultancy costs plus investment costs were compared with the value of energy saving (derived from the energy audit). Similar to (Jordal-Jorgensen 1995), cost-efficiency was calculated for 2 different perspectives: private economic (economic gain of the client using market prices and excluding subsidies) and socio-economic (costs from external environmental effects – marginal abatement costs of CO2, SO2 and NOx). The aim was to identify who gain and who loses from the different energy auditing schemes: the client, the society or the consultant. The free-rider effect was also taken into account, in order to exclude investments in energy efficiency that cannot be attributed to energy audits.

Results from the analysis of 5 energy auditing schemes: Heating Consultancy (buildings above 1500m2 and 120 kW boilers), Energy Consultancy Scheme (for single-family houses), Oil burner registration (oils burners lower than 120 kW), Electricity audits in large industries (Industries with electricity consumption between 5 and 50 million kWh/year) and Electricity audits in small industries (Industries with electricity consumption between 1 and 2 million kWh/year), were the following:

Actual energy savings is much smaller than the so-called technical potentials (1 to 5% per annum for households, 3% per annum for electricity use in large industries and 4% per annum for electricity use in small industries);

The only scheme yielding positive results (both socio-economic and private) is the Electricity audit in large industries scheme;

In Australia the results of a survey to 100 Australian businesses that participated in an energy auditing programme, which subsidised 50% of the cost of the energy consultant fee, is presented in (Harris et al. 2000). The main aim of this study was not to assess the cost-effectiveness of energy audits, but to investigate the factors that influenced companies to invest in energy efficiency, particularly why recommendations of energy audits are sometimes ignored and what is the actual uptake of subsidised energy audits. From the results of the survey to businesses it was possible to conclude that:

80% of the energy audits recommendations were implemented in an average of 6 recommendations per site;

Companies stated that energy audits were worthwhile;

The auditing scheme was probably cost-effective to the companies (Net Present Value analysis performed does not include hidden and other transactional costs);

Audits are worthwhile to many businesses even without government subsidies;

Promotion of energy efficiency should concentrate on the desirability of a firm taking, what the authors named an - enterprise-wide view of their energy efficiency, perhaps suggesting that an expert be consulted.

Another study is presented in (Gruber et al. 2003), and although it is focusing on the barriers towards the uptake of energy efficiency in SME's, it includes results some results that are important in the discussion of the effectiveness of energy auditing programmes. In Gruber's research econometric techniques were used to assess the determinants of the barriers to energy efficiency for the German commerce and service sectors, mostly public and private SME's. The main aims of this research were to estimate the importance of different barriers to energy efficiency for German companies and to test if there is empirical support to the claim that energy audits are an effective means to overcome barriers to energy efficiency in SME's as often suggested. This research was based on a survey, of 2848 managers of enterprises and public institutions, which included questions on economic and technical factors that affect energy use and also questions about energy management, measures taken and obstacles for energy efficiency. In the regression analysis, energy audits were considered to be an independent variable that took the value 1 if an audit had been carried out (other independent variables were also considered, such as company size, sub-sector and energy consumption).

The barriers to energy efficiency or dependent variables were: lack of time, lack of information about energy consumption patterns, lack of information about energy efficiency measures, company investment priorities, uncertainty about future energy prices, landlord/tenant dilemma. The findings of this study suggest that:

Energy consumption, size and audit exhibit an expected negative sign even when they are not statistically significant;

Carrying out an energy audit will help reduce the barriers to energy efficiency analysed;

Lack of time appears to be a problem to all sub-sectors analysed (except for public or quasi-public organisations);

Lack of information about energy efficiency measures appears not to be a problem for any sub-sector in particular;

Organisational priorities appear to be biased against energy efficiency in small industrial and commercial enterprises, when compared to other sub-sectors;

The landlord/tenant dilemma seems to be a problem for half of the sectors analysed.

Another important result presented in this paper was that past experience on energy consultancy programmes showed limited success to small grants for energy audits in SME's. Apparently most of the companies preferred a short but cost-free initial audit and wanted to pay the follow-up detailed audit on their own as soon as a reliable estimate about the saving potential existed. Nevertheless it is stressed that energy audit programmes for SME's should not be too complicated and require companies to fill out tons of forms for which they don't have time.

Recently, an evaluation of the Danish free-of-charge energy audit programme was conducted and it was presented in (Dyrh-Mikkelsen et. al 2005). This energy auditing programme exists since the early 1990s, and it provides energy free-of-charge energy audits to all enterprises with electricity consumption above 20 MWh/year. The programme also promotes other energy efficiency activities and campaigns. A comprehensive evaluation of the free-of-charge energy auditing programme was performed in 2004, using the Danish evaluation guidebook which aimed to assess the cost-effectiveness of the programme from various perspectives, the government use of public money to subsidised energy audits, consumer satisfaction and the cost-effectiveness from the society point of view. From the three different complementary evaluation methodologies it was possible to conclude that:

About 48% of the identified energy savings potential has been realised, and that the simple payback of this implemented measure is in average 3.6 years;

It was not possibly to confirm that a reduction of electricity consumption (or stagnation) takes place after an energy audit compared with a control group that has not received an audit, based on the data available (the analysis was inconclusive);

In a small sample of 10 case-study enterprises, considered to be success examples of the programme, 5 to 6 advices were received and in the total of 56 advices received, 36 were implemented. Implemented measures are the ones that have a shorter payback period;

Another important conclusion of the study, if not the most important, was that the potential savings and investments relied on estimates included in the audit reports, and that it was important to have metered data, from automatic metering systems, in order to have more conclusive results of the evaluation.

From the review above, the cost-effectiveness of most of the reviewed energy auditing programmes is not conclusive and unfortunately the causes of the apparent low cost-effectiveness of the programmes are not clear. However, it may be possible extrapolate that (short) free energy audits can be a driver for improved energy efficiency and therefore energy auditing programmes can be considered a valid instrument for the reduction of CO2 emissions. Therefore, it is important to assess the cost-effectiveness of the energy auditing process, i.e. of the approach, the methodologies, the techniques and the tools used by energy auditors.

Increasing the cost-effectiveness of building energy performance assessments

The cost-effectiveness of energy audits was described in an European Commission - Joint Research Centre (JRC) study presented in (Heckle et al. 1990). They analysed the results of energy audits carried out by 4 different consultants from 3 European countries (France, Italy and Switzerland) on the same set of buildings. The objective was to compare commercial energy auditing methods from the point of view of accuracy and cost-effectiveness. Audits were compared not only to each other but also to a more detailed benchmark survey conducted by JRC researchers. Large differences were found between the results of all the audits, what might result from the different methodologies used by the different consultants.

However, no audit was consistently very much worse or better than the others. Furthermore, the benchmark study identified a considerable number of potentially cost-effective energy-saving measures, which were completely overlooked by commercial audits. Consultants based their recommendations on a relatively small number of common energy saving opportunities, which may indicate strong reliance on general checklists. (Heckle et al. 1990) found no correlation between the level of detail and cost of the audit and its overall cost-effectiveness, and that energy consultants tended to base their recommendations on a relatively small number of common energy saving opportunities, which may indicate strong reliance on general checklists.

Supported by the results of the studies presented above, researchers called for an expert system for large scale energy auditing in buildings (Caudana et al 1995). A prototype of an informatics tool was developed for improving the energy auditing in existing buildings named BEAMES (Caudana et al 1995). This tool is knowledge-based software with different functional modules (statistical module, pattern association, candidate energy saving opportunities list, analytical evaluation of energy savings, etc.). The tool was intended to be a support and field guide for professionals (engineers, architects, technicians) on the field, building energy saving companies and energy utilities involved in Demand Side Management (DSM) programs. One of the mains aims of developing this tool was to improve the quality of energy audits (and its cost-effectiveness) by: reducing the time for pre-audits, reducing the time for compiling reports and enabling consultants to have more time to perform on the field measurements to specific targeted areas of expected energy saving opportunities (identified in the pre-audit).

The methodology for assessing building energy performance under BEAMES is quite simple. Initially there is a pre-audit phase allowing the auditor to know the necessary level of complexity (and cost) of

the audit and supply a list of candidate energy saving opportunities on which the auditor could focus his attention and plan appropriate measurements. After the pre-audit phase is completed the BEAMES provides guided assistance for measurement techniques, audit procedures and implementation strategy options (using several databases of building standards, images, videos and internet resources). A follow up of BEAMES research outcome was THEBIS – Thermie European Buildings Information System (http://thebis.jrc.it). THEBIS is a database containing details of the most advanced and successful European building demonstration projects, which is only a module of what would be the BEAMES software tool. Apparently no further developments were made on the development and application of the BEAMES prototype.

Another European project developed an energy auditing tool to be used directly by the energy end-user. The Self-Help Energy Efficiency Business Advisor (SHEEBA) software package was developed in order to help small businesses in the identification of energy saving opportunities, (Fleming et al. 2000 and 2002). The software provides a wide range of information on energy management issues, energy analysis tools and a reporting facility of potential energy efficiency improvements and energy cost reductions. The objective is to convey the knowledge and experience from energy surveys with powerful energy analysis techniques in a cost-effective way to SME's and others involved in promoting energy efficiency. SHEEBA has two main elements:

Site specific advice - audit and energy analysis tool

The software uses what is called energy analysis techniques of first resort, described in the UK's Energy Efficiency Best Practice Programme Good Practice Guide 125 – Monitoring and Targeting for small and medium sized companies (ETSU et al. 1998). The input is energy (electricity, gas, etc) consumption – for a minimum period of at least 12 months, production and degree-days information. It will then identify relationships between these quantities and display the results of the analysis on the screen in the form of charts and tables. The user can also fill out a questionnaire that is based on surveys checklists for identifying the most common energy savings opportunities found by consultants.

General advice – quiz, glossary and encyclopaedia of energy terms

The glossary provides the definition of a wide range of energy terms and the encyclopaedia uses text, images and videos to describe different aspects of energy efficiency measures. The CD-ROM encyclopaedia contains information on equipment: such as boilers, lighting, compressed air systems, motors, monitoring and targeting techniques, and a section on energy science history. There is also a quiz available, providing entertainment whilst testing users' knowledge of energy efficiency issues.

The SHEEBA software was tested on a wide range of small businesses and buildings in the UK, Spain and Portugal, and it was found that there are alternative approaches to taking a consultant to a site to identify energy saving opportunities. Furthermore, the CD_ROM proved to be a very effective way of distributing energy efficiency advice to businesses. However, the energy analysis tool had some limitations, particularly if the energy consumption data used was derived from estimated readings.

There are other tools and software packages for energy auditor and practitioners, which aim to improve the quality and cost-effectiveness of energy audits. A review of energy auditors tools used in European countries can be found in (Väisänen, H et al. 2003). These tools are usually developed according to the needs of the aims of the energy auditing programme, but more importantly, these tools have to take in consideration the existing audit market and consultancy market. Usually the best approach is to combine a different energy auditing tools, such as guides, handbooks, check-lists, software tools, benchmarking or even data bases on energy conservation options.

Currently, energy and water data in short- time series (usually in half-hourly, quarter-hourly intervals) is becoming easier and cheaper to get, and it is now available to a large number of buildings and sites. In addition, the advance in technology has been decreasing the cost of automatic energy and water metering hardware and software in the last few years, will lead to an increasing use of this technology in building energy assessment. In fact, the proposal for a Directive on End-Use Efficiency and Energy Services, in its Article 13 states that Member States will need to ensure accurate and informative metering and billing of energy consumption, and this will only be possible if advanced metering technology and intelligent monitoring analysis techniques will be place. Therefore in the near future it would be expected to have extended metering of buildings, in particular non-domestic buildings.

On the other hand, one could argue that there is a significantly large potential for the application of metering technology and short time series energy and water data in building performance assessment. In addition the use of this data together with advanced analysis techniques could be used to develop instruments to improve the cost-effectiveness of conventional audit schemes. This is required by the proposal for a Directive on End-Use Efficiency and Energy Services, in its Article 12. Trial approaches on the use of electricity short-time series data and innovative analysis techniques have already been tested on non-domestic buildings, in UK office buildings (Ferreira et al. 2003) and UK secondary schools (Stuart, Fleming, Ferreira and Harris, in press).

The experience of the Leicester energy agency suggests that energy audits by themselves were not the best tool for building energy management. They employ a different methodology for the identification of savings and evaluation of energy efficiency and renewable energy projects. The collection and analysis of half hourly electricity, gas and water data, using an intelligent energy and water metering and monitoring system in their municipal buildings.

In conclusion, energy audits are important, however energy management is a continuous process, and energy auditing has to be effectively combined with automatic metering systems and monitoring and targeting techniques/software in order to achieve the best results.

Intelligent energy and water monitoring in Leicester City Council buildings

A new approach for assessing energy and water performance assessment in buildings based on the use of metered (half-hourly) data. Data is collected by the monitoring and targeting system using an automatic meter reading system, information technology and energy analysis software. An overview of the energy and water monitoring and targeting system used in Leicester City Council buildings is presented and assessed in terms of its cost-effectiveness.

Leicester City Council collects utility data using a proprietary system which combines information technology and proprietary software package. Electricity, gas and water meter readings are taken at half hourly intervals and usually recorded onto a data logger locally. Data is also collected from district heating heat meters and from automatic weather stations. Each day the 48 readings from each (electricity, water and gas) meter are transmitted by low power radio to one of seven main receivers, similarly to the system presented in (DETR 1996). The main receivers then forward the data on to a central receiver located in the energy office where it is stored and analysed. It is possible to test the relationship between energy use and weather and/or occupancy. The proprietary software is used to plot it as charts at various resolutions; it also provides regression analysis and generates alarms when consumption falls outside predetermined levels. In summary the proprietary software main features are:

Graphical display of data (including profiling with target setting);

Regression analysis with degree-days (assess weather related consumption);

Cumulative sum of the differences from an existing pattern of consumption;

Year on year comparison;

Reporting functions, including exception reporting.

Currently the Leicester City Council system collects and performs analysis on gas, electricity and water data for 223 buildings, including:

Schools

Libraries

Leisure centres/Swimming pools

Administration offices

Elderly persons homes

Warden assisted accommodation

Maintenance depots

The cost to set up the energy and water metering and monitoring system is of the order of € 2,000 per site, but it can be as high as € 12,000 in more complex sites, where many sub-meters need to be replaced.

To date the system has identified problems that have been implemented and have led to annual savings of approximately 40,000 cubic meters of water, 670,000 kWh of gas and 135,000 kWh of water. This equates to a saving of around € 100,000. In addition to this, a further € 100,000 of savings has been identified that are yet to be implemented. Identified savings are mainly in the form of water leaks, overnight consumption and heating control problems that may remain undetected if it were not for the half hourly metering. The benefits of this system are that it identifies the potential for investment, it assists in diagnosing a problem and it allows potential savings to be accurately quantified. It should be noted that the data monitoring does not generate savings itself, it simply highlights waste and assists in the diagnosis of waste where it already exists. This kind of data monitoring allows for focused energy audits to be performed where a known problem exists. It even allows the timing of a visit to be chosen to ensure the phenomenon under examination is occurring at the time.

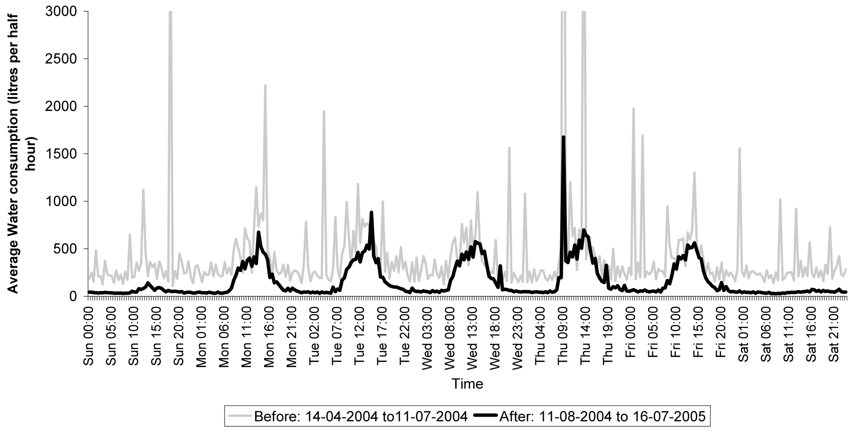
Application examples of the intelligent energy and water monitoring system

A number of example cases of energy and water savings detected, corrected and verified using Leicester City Council intelligent energy monitoring system are presented in the following section

Community College

This building had high overnight consumption and on investigation it was found that the urinal controls were faulty. These were replaced on 8 urinals at a cost of € 2,300 and the overnight consumption fell by equivalent to € 7,670 per year. The following chart presents the situation before and after the corrective action was taken.

Average water consumption profiles before and after replacing urinal controls

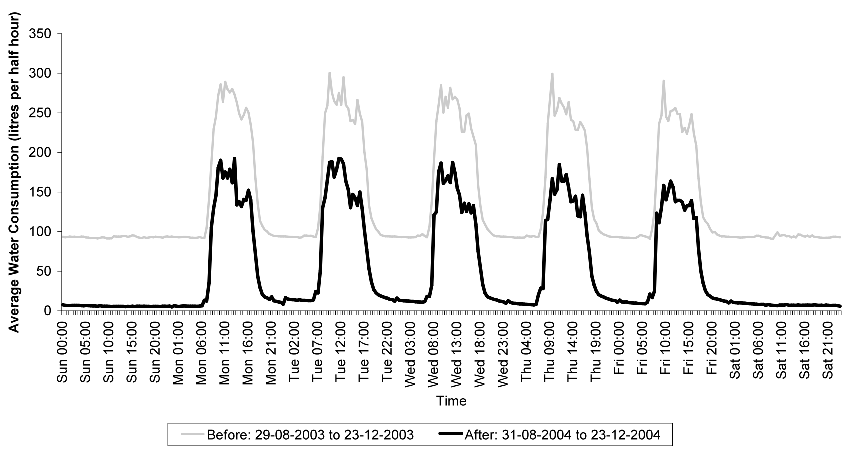


The data also shows a reduction in spikes, this may be due to the same measure or simply due to raised awareness of the potential savings to be made from water conservation.

Administrative building

Again high overnight consumption led to an investigation that identified a water leak. The leak was fixed resulting in a saving of about €3,850 per year.

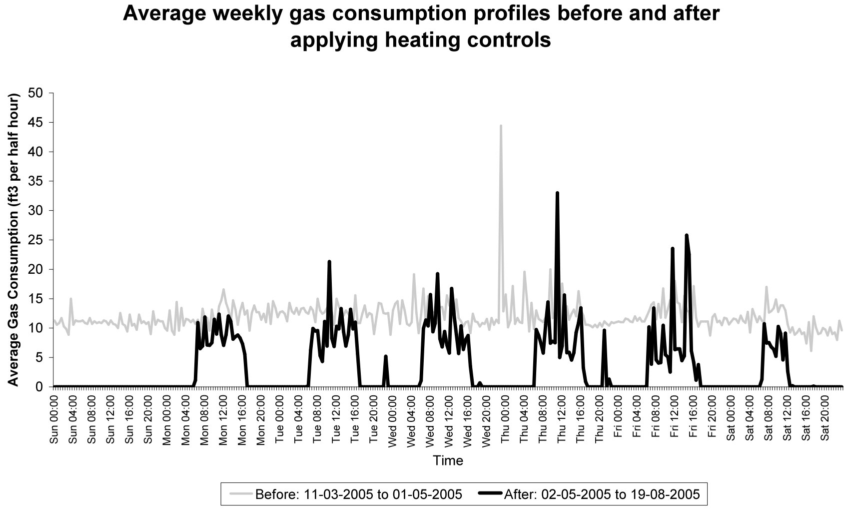
Average water consumption profiles before and after repairing leak



Housing Office

Once again, the simple method of comparing overnight consumption with peak load highlighted this one for investigation. It had been operating with no heating timer.

Installation of a timer reduced overnight consumption to zero and saved about €2,250 per year.



Other applications and futures uses

Another application of this system was to use the collected data into in Display™ Campaign simulation tool in order to calculate and more importantly classify the building according to its energy and water performance. Display™ Campaign is within the scope of the Directive on the Energy Performance of Buildings, (Schilken et al. 2005). Display is a certification scheme for municipal buildings and also an information tool to raise the public awareness of energy consumption. Leicester municipality is one of Display's pilot partners. The most visible part of Display is a poster, based on the now well-known principle of energy labels for household electrical appliances and which has been adapted for use on public buildings. It features a range of classes from A to G for the overall primary energy consumption, the resulting CO2 equivalent emissions, and water consumption. In 2005, Leicester had conducted the building energy and water performance classification of 100 municipal buildings using Display. Buildings energy and water performance assessment was conducted using real (metered) energy and water consumption data.

Leicester City Council is using the metered energy and water consumption short time series data to develop training materials in the interpretation of the data by occupants, which ultimately will promote behavioural changes and energy savings with high cost-benefit.

Conclusions

Energy audits are an essential instrument for building (and industry) energy management, and the promotion of end-use efficiency and renewable energy. However, there is room for innovation in this field, particularly in what concerns the methodology, the techniques, and tools used by auditors. There is the need to guarantee the overall effectiveness of the auditing process that is aiming to improve energy end-use efficiency, i.e. implement energy saving measures (water savings, renewable energy technologies, etc.).

The cost-effectiveness of most of the reviewed energy auditing programmes is not conclusive. There is no clear indication of how cost-effective are energy auditing programmes, nevertheless it may be possible to increase the quality and the cost benefit of energy audits, and consequently of the auditing programmes in general by using instruments and tools that will reduce the auditors time on site, transactional costs and other costs inherent to the energy auditing process. Furthermore, evidence was found that that (short) free energy audits can be a driver for improved energy efficiency and therefore energy auditing programmes can be considered a valid instrument for the reduction of CO2 emissions.

Energy management is a continuous process, and in order to have sufficient information to measure and evaluate energy savings it is necessary to have in place a reliable energy and water monitoring system. From the analysis of the preliminary results of Leicester City Council intelligent energy and water monitoring system it is possible to conclude that the analysis of readily available short time period metered data and advanced energy analysis techniques, can help identify energy saving opportunities in non-domestic buildings. This should be particularly useful for the implementation of the Directive on Energy Performance in Buildings and the future Directive on End-Use Efficiency and Energy Services.

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Acknowledgements

The authors would like to acknowledge the help of Prakash Patel, Peter Webber and Stewart Conway from Leicester City Council.