



Programme Area: Distributed Energy

Project: Macro DE

Title: Development of a methodology to calculate energy demand

Abstract:

This deliverable is number 1 of 3 in Work Package 2. Its objective is to develop a methodology for forecasting energy demand profiles across residential and tertiary (light industry) properties in a given geographical area. In addition the report estimates the level of confidence in the methodology. The demand profiles generated form the basis for demand aggregation modelling in Work Package 4.

Context:

This project quantified the opportunity for Macro level Distributed Energy (DE) across the UK and accelerate the development of appropriate technology by 2020 for the purposes of significant implementation by 2030. The project studied energy demand such as residential accommodation, local services, hospitals, business parks and equipment, and is developing a software methodology to analyse local combinations of sites and technologies. This enabled the design of optimised distributed energy delivery solutions for these areas. The project identified a number of larger scale technology development and demonstration projects for the ETI to consider developing. The findings from this project is now being distilled into our Smart Systems and Heat programme. The ETI acknowledges that the project was undertaken and reports produced by Caterpillar, EDF, and the University of Manchester.

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Development of a methodology to calculate energy demand

Macro Distributed Energy Project
Project task 2.0

A report prepared for the ETI

Version 2.0
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Executive Summary

The UK's commitment to an 80% reduction in greenhouse gas emissions by 2050 and 34% reduction target by 2020 will require significant carbon reductions from electricity, heating and transport. While there is no single solution, Distributed Energy (DE) offers a proven way to maximize the efficient use of our natural resources for heating, electricity and cooling delivery. Deployment of DE is a cornerstone of the UK Government energy policy and is strongly supported by Regional Development Agencies (RDAs) and Local Authorities, however there is no clear pathway for achieving the targets and requirements for efficiency nationwide.

The goal of this project is to characterise the temporal energy demand across a complete geographic subdivision of the UK and link the supply capabilities of DE equipment through a software tool to develop optimized DE Solutions.

The transition from small-scale, site by site based DE solutions within a region to medium to large-scale DE schemes has the potential to overcome a number of technical and commercial challenges. For example, the aggregation of a diverse range of end user energy demand profiles will assist in levelling demand fluctuations and has the potential to improve the economics and operability of distributed energy systems.

Based on a method developed by EDF and data that EDF has sourced, the approach has produced aggregated demand results that have been compared with 2 sources of data from real measurements. Annual energy demand has been calculated across the district of Harrogate, compared with DECC consumption data and plotted as error scatter graphs. The results showed random errors in residential thermal demand calculations of approximately 10% (annual electric demand will use DECC's data directly). The tertiary demand calculations contained a larger uncertainty of approximately 30%. Hourly thermal load has been calculated for a district heating project, "CHP Ops", and compared with the measured load to give an indication of the likely hourly and daily prediction error. The results on residential load showed an error of 13% at a daily level and 22% at the hourly level. The tertiary predictions had larger errors but the building sample was too small to draw sound conclusions from.

We believe that the methodology for the residential thermal demand is sound and there is sufficient data such that a 10% uncertainty is reflective of the potential propagating error for the UK. While the tertiary sector data methodology is sound, there are two key issues with the data sets that may cause the larger error:

1. The registered company information databases used in the tertiary sector demand calculations contain many records that are missing the number of employee data;
2. Conversions between employee numbers and building floor area can only currently be performed at large tertiary sector groupings.

The contribution of demand uncertainty from the tertiary component could be projected and tracked in the resulting demand calculations.

The temporal resolution of the demand is good and the method, based on energy transporter load prediction techniques, seems able to predict the main trend and features of residential thermal demand.

In a separate report, a recommendation was made to purchase CreditSafe's registered company database due to its better overall accuracy of key indicator data for the tertiary sector.

Contents

Executive Summary	2
Glossary.....	6
1. Introduction – background, objectives and scopes.....	7
1.1. Background	7
1.2. 2.0 Task Objectives	7
1.3. Scope of the study	7
1.4. Structure of the report	8
1.5. Additions in Version 2.0 - extension work on the Demand Methodology	8
2. Demand Modelling Approaches.....	9
2.1. Forward modelling	9
2.2. Data-Driven modelling.....	9
2.3. Mathematical description	10
2.4. Top-down vs. bottom-up strategies.....	10
3. Trial methodology of energy demand calculation.....	11
3.1. Proposed Trial Methodology.....	11
3.2. Residential Energy Demand.....	12
3.3. Non-residential Energy Demand.....	13
3.4. Modelling Temporal Residential Thermal Demand.....	15
3.5. Industrial Excess Heat.....	24
3.6. Space cooling for the commercial sector	26
3.7. Industrial electricity.....	26
3.8. Working Assumptions.....	27
4. Demand Related Data Sets	30
4.1. Overview	30
4.2. Indicators.....	30
4.3. Benchmarks.....	31
4.4. Profiles	32
5. Validating Demand Calculations	33
5.1. Annual Demand Calculation for Harrogate	33
5.2. Calculations for “CHP Ops” Cogeneration and District Heating Site	35
6. Statistical Analysis	42
6.1. Introduction and Approach.....	42
6.2. Assumptions	42
6.3. “Bottom-Up Analysis” of Likely Errors	43
6.4. “Top-Down” Harrogate MLSOA statistics	47
6.5. CHP Ops prediction errors	50
7. Discussion	52
7.1. Statistical Analysis	52
7.2. Confidence in the Demand Prediction	53
7.3. Further Validation Data Investigations	56
8. Conclusions	58
9. Recommendations	59
Recommendations for additions to task 2.0 “Demand Calculation Methodology”	59

	Recommendations for task 2.1 (Formation of Characteristic DE Zones).....	59
	Recommendations for task 2.2 (Characterisation of industrial waste heat).....	59
10.	Future Work	60
	Demand Zone Creation and Clustering.....	60
	Classification into “Characteristic” Zones	60
	Waste Heat Mapping.....	60
	References	61
	Appendix 1: WP2.0 Acceptance Criteria	63
	Appendix 2: Method To Restore Missing Employee Data	64
	Appendix 3: Profile Set Descriptions.....	66
	Appendix 4: Further Validation Data Sets	72
	Appendix 5: Gas Consumption and Thermal Demand	78
	Appendix 6: Tertiary Profiles.....	79

Glossary

Term	Definition
Benchmark	An energy benchmark is an expected value for energy consumption. For residential and non-residential sectors these benchmarks are either collected from CIBSE or are derived from EDF proprietary data.
CIBSE	Chartered Institute of Building Services Engineers
Combined Heat and Power (CHP)	The production, supply and use together of electricity and heat.
Demand Centre	Premises having an Energy Demand. (See also Site).
Distributed Energy (DE)	Distributed Energy systems are those systems supplying energy, which as a minimum may include electricity, heat and/or cooling, locally and/or directly into the electricity and heat distribution systems (rather than the transmission system).
Medium to Large Scale DE Systems	For the purposes of this Project, Medium to Large Scale DE Systems are defined as those generating or consuming, individually or when aggregated, 100 kW _e – 50 MW _e . The scope of Zonal DE Systems considered shall include as a minimum: prime movers and generators of electricity and heat; generator connections to the electrical and heat distribution systems; Zonal heat distribution piping; Site connections to the electrical and heat distribution systems; and Site and Zonal metering and control systems.
Energy Demand	A demand for energy, which as a minimum may include electricity, heat and/or cooling.
Excess Heat	Residual heat potential that can be offered to third parties (e.g. heat network, other company, ...) after internal use on the industrial site.
Energy Supply	A supply of energy, which as a minimum may include electricity, heat and/or cooling.
Geographical Area	The areas defined by existing geographical and statistical divisions of the UK i.e. Middle Layer Super Output Areas (MLSOAs) for England and Wales, and Intermediate Geographical Zones (IGZs) for Scotland.
IGZ	Intermediate Geographical Zone
Indicators	Indicators are basic parameters that are directly related to energy demand and represent the basis for energy demand calculations. The residential and non-residential energy indicators are collected from EDF as well as from commercial data vendors.
ISIC	International Standard Industrial Classification
LLSOA	Lower Layer Super Output Area, as defined by UK Government
MLSOA	Middle Layer Super Output Area, as defined by UK Government, is part of geographic hierarchy that covers England and Wales. Every MLSOA consists of minimum 5000 population or about 2000 households. More information at: http://www.berr.gov.uk/files/file40044.pdf
NACE	Classification of Economic Activities in the European Community
NAF	Nomenclature des Activités Françaises (French NACE)
SIC	Standard Industry Code
Zone	A Zone is a combination of Sites whose Energy Demand may be aggregated, typically in the range 100 kW _e – 50 MW _e , to enable optimised Distributed Energy delivery solutions.

1. Introduction – background, objectives and scopes

1.1. Background

Increasing awareness of cost effective energy systems, highly efficient energy use, secured energy supply as well as concern about CO₂ emissions are encouraging policy makers and energy companies to search for alternative energy solutions in the United Kingdom (UK). Distributed Energy (DE) and Combined Heat and Power (CHP) can help to achieve these goals. By identifying site specific and locally sourced energy demand patterns and potential waste heat sources, it is possible to aggregate demand zones of similar pattern. In this way the deployment of DE or CHP systems becomes more cost effective and environmentally efficient.

The broad objective of the Macro-DE project is to assess the opportunity for providing low carbon distributed energy solutions for similar aggregated energy demand zones across the UK. This project will investigate current approaches to demand aggregation, calculate energy demand profiles and recoverable industrial waste heat across the UK. After identifying about 10 – 20 “characteristic” demand zones, it will estimate the deployment and CO₂ reduction opportunity for DE systems in those zones and calculate the UK benefit due to a zoning approach and the use of waste heat.

1.2. 2.0 Task Objectives

The main objective of this task is to develop and estimate the level of confidence in a methodology for energy demand profile calculations. The specific objectives are to:

- Develop a methodology to calculate energy demand on an MLSOA basis and to check whether this methodology is scalable to the whole UK.
- Carry out statistical analysis to quantify the level of uncertainties within the result
- Validate the result
- Recommend on the refinement of Task 2.1 and 2.2 methodologies
- Compare the MarketSafe and GeoPlan registered company datasets (provided in a separate report).

The acceptance criteria for the task are described in Appendix 1.

1.3. Scope of the study

In scope:

- Thermal and electricity energy demand methodology of the residential and tertiary sectors per MLSOA
- Development of hourly load demand for residential and tertiary sectors
- Development of a methodology to assess the industrial waste heat and its scalability across the UK
- Aggregated annual and temporal energy demand for sample MLSOAs
- Predicted load on a district heating network
- Statistical analysis and validation of the result (quantification of uncertainty)
- Comparison of MarketSafe and GeoPlan UK company data

- A report detailing all the methods and analysis of results

Not in scope

- Cooling energy demand for tertiary sector
- Industrial demand
- Waste heat profiles

1.4. Structure of the report

In Section 2, demand modelling methods are discussed.

In Section 3, the methodology to calculate the residential, tertiary energy demand is explained. A specific section is devoted to methods for aggregated residential thermal demand profiles. An approach to calculate the industrial waste heat across the UK is also proposed.

Section 4 describes the data sets used in the demand calculation methodology.

Section 5 describes the validations performed against measured data.

Section 6 describes the statistical analysis to identify and to quantify the uncertainties/errors within the methods and results.

Section 7 discusses the outcomes of the statistical analysis, the confidence in the demand methodology by component and reviews further potential validation datasets.

Sections 8, 9 and 10 draw conclusions, provide a number of recommendations for further investigations and describe the next tasks.

1.5. Additions in Version 2.0 - extension work on the Demand Methodology

This version of the report builds on version 1.0 and describes the extension of the originally proposed demand calculation method. The additional elements in this report are listed below.

- A detailed description of residential thermal demand modelling – sections 2 and 3.4.
- An improved residential electric demand method – section 3.2
- A method for restoring tertiary indicator data – section 3.3
- Detailed residential and tertiary demand profiles – section 4.4
- Validation of the temporal demand prediction – section 5.2
- Statistical analysis of the temporal prediction accuracy – section 6.5
- A discussion of the level of confidence that the method delivers – section 7.2
- A review of potential validation sites – section 7.3

In addition, most of the sections have been revised and further detail has been added in six Appendices.

2. Demand Modelling Approaches

2.1. Forward modelling

The different models available can be differentiated by their approach. The forward or classical approach is applied to predict output variables. With readily available computing power, complex models have been realized along this line of thought to include natural phenomena and interactions within the system. A forward approach delivers a more or less complete representation of the physical world (ASHRAE 2005). Heller (Heller 2002) classifies this category as deterministic modelling. On the scale of buildings it is the most common approach to describe and predict the energy use. This category of models includes dynamic thermal simulations such as EnergyPlus, DOE-2 and TRNSYS (ASHRAE 2005) as well as steady-state or quasi steady-state models as specified by EN ISO 13790. This approach is sometimes also referred to as a white box model with the limitation that a pure white box model could be seen as a copy of reality and therefore cannot exist (Tarr 2009).

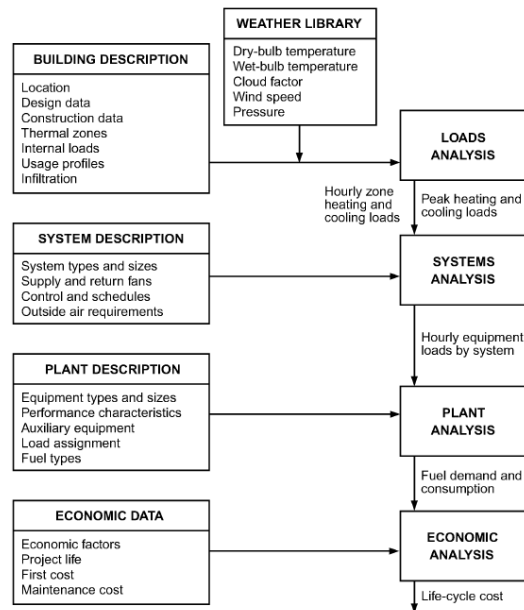


Figure 1. Flow chart for building energy simulation program; (ASHRAE 2005) after (Ayres, Stamper 1995)

Despite the great variety in the complexity of the forward models, the general principle for estimating the energy requirements, as depicted in Fig. 1, consist of the load calculation which is then translated into a system or secondary equipment load that incorporates losses in the distribution and auxiliary systems. Finally the primary energy requirements are calculated i.e. the requirements of the energy conversion system using fuel or electric energy. Adding economic data to the model allows for the economic analysis of the system.

2.2. Data-Driven modelling

In contrast to this the data-driven or inverse approach uses input and output variables that are known and measured to determine a mathematical description of the system. This obviously requires that the system has already been built and measurements have been made. In practice data-driven models tend not only to be simpler to use but also more accurate (ASHRAE 2005).

Amongst the data driven modelling approaches a widely used approach is the empirical or black box approach (Heller 2002). A black box model defines the input output relation without describing physical properties of the modelled process. Black box models are fast but sometimes inflexible in their application. Therefore by their empirical nature these models do not require an understanding of the underlying processes. Once established and tested they therefore do not require a large knowledge on the user side.

2.3. Mathematical description

While the description of forward and data driven approaches includes concepts of stochastic and non-stochastic models, an important distinction regarding mathematical descriptions are steady-state and dynamic models (Koch, Harnisch, Blok 2003).

Steady-state models include single-variant models typically using ambient temperature as the one regression variable. To adapt the function to the actual operation these can include one parameter only or multiple parameters. On the other hand dynamic models are used with hourly or sub hourly data for those applications where the effects of the building's thermal mass play a significant role. While dynamic models are useful for detailed description of the system and the interrelated effects within, dynamic models tend to have a higher complexity and require more detailed data for data-driven as well as for forward models (ASHRAE 2005).

2.4. Top-down vs. bottom-up strategies

In the wider discussion of modelling approaches, the classification of top-down and bottom-up approaches are used. These reflect the detailed descriptions of individual entities in the system (bottom-up) or the description of the overall system where only conclusions concerning the central system can be drawn (Heller 2002). Even though many examples of top-down modelling apply data-driven models while bottom-up strategies tend to employ forward models in principle the differentiation refers only to the internal set up of the model.

Related to this wider discussion of a model's strategy is the general objective. Simulation models usually apply a bottom-up approach to describe the energy system by adding single processes to process chains or networks. In contrast optimization models tend to focus on the cost function. Usually simulation models are applied to quantify the technical or techno-economic potential for energy savings or emission reductions (Koch, Harnisch, Blok 2003). In the detailed description of simulation models expert knowledge replaces the purely mechanistic approach pursued by optimization models. Thus technical measures can be discussed on a more detailed level. Even though the approaches follow clearly different paths (Koch, Harnisch, Blok 2003) it should be noted that with an increasing number of bounds, the optimization approach is eventually transformed into a simulation.

In the following, a demand calculation based on benchmarks and indicators is described. This is combined in a second step with a distribution model using annual energy demand values. These are the output of the demand calculation as an input value to generate a profile consisting of daily demand values over one year. The energy signature model used is further described in Section 3.4.

3. Trial methodology of energy demand calculation

3.1. Proposed Trial Methodology

The annual energy demand is calculated separately for each of the many residential and tertiary sectors separately for the thermal and electricity demand. The energy contributions from the sectors are then distributed by associated normalised profiles. The normalised profiles are scaled by the energy contributions associated with them. Afterwards, these are all combined to give the total thermal and electrical load curves for the sites within a specified region.

Equation 1 below describes the calculation of the energy demand (thermal or electric):

$$\text{temporal energy demand} = \sum_{\text{sector}} \sum_{\text{sites}} (\text{indicators} \times \text{factor} \times \text{benchmarks}) \times (\text{profile}) \quad (1)$$

The *Indicators*, such as number of residential buildings or number of employees working in tertiary sectors, consist of basic data that are directly related to energy demand. The *Benchmarks* are median standards for energy intensity values (collected from secondary sources or derived for this trial) that convert the indicator data into energetic values. Conversion *Factors* may be required to change the indicator variable into the intensity factor; for example number of employees into floor area. The *Profile* data is a normalised series of values that distributes the annual demand temporally.

Figure 2 describes the general method applied to estimating annual demand in this study.

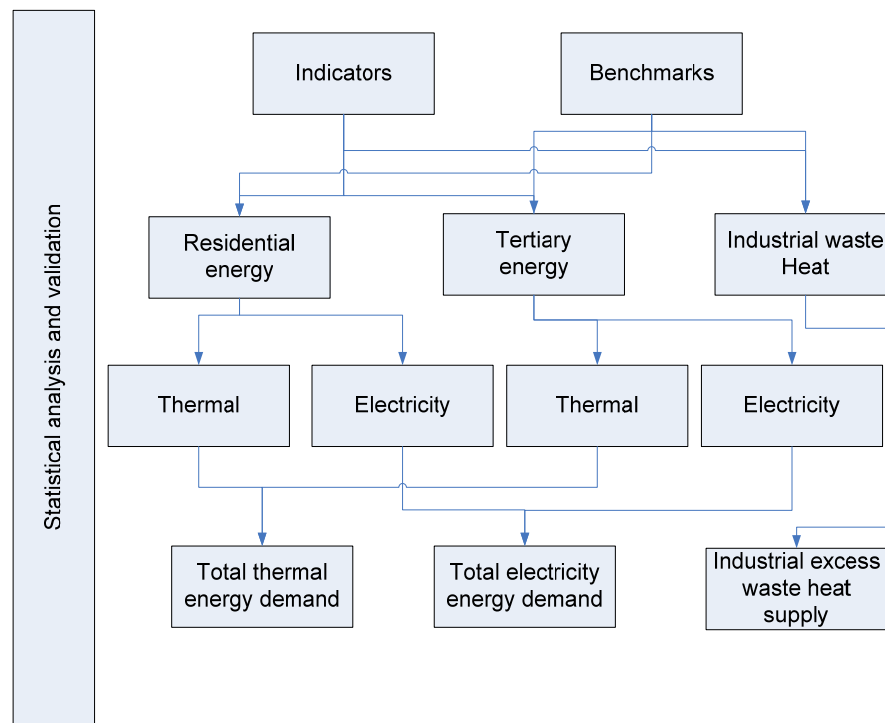


Figure 2. Trial methodology approach for the calculation of annual demand

3.2. Residential Energy Demand

The residential energy demand is calculated based on Equation 1. This section explains the detailed use of different indicators and benchmarks data in the calculation (Figure 3).

Residential thermal demand is mostly dependent on the number and type of buildings in a region. Therefore, residential housing stock data for all the MLSOAs in the UK is collected from EDF Energy UK. This dataset is categorised according to five housing types and seven age classes (see Section 4 for further details).

The housing types are matched to corresponding residential benchmarks for thermal demand. The benchmarks have been extracted from values developed for a proprietary EDF tool that can predict customer savings from energy efficiency measures (see Section 4 for more detail on these benchmarks). The tool uses detailed information on the housing types, number of bedrooms, construction ages, electricity and gas consumption, etc. Considering an average gas boiler efficiency of 80%, a total of 35 thermal benchmarks are derived.

The benchmarks are then weather adjusted per region according to the approach in CIBSE’s TM46 guidelines (CIBSE 2008), which uses a pro-rated degree-day (base 15.5 deg C) scaling. The thermal scaling value recommended for residential buildings is 55%.

Electricity demand was initially calculated according to the same approach, shown in Figure 3 below. In the revised, *extension*, method the residential electric demand is decomposed according to tariff: Standard or Economy7. These two consumption classes are compiled by DECC per MLSOA (DECC, 2008) and can be used directly without needing extra electric demand benchmarks.

A set of hourly residential profiles were used to distribute the annual residential demand by day and year. In each case, the total demand was associated with the appropriate profile class. Typically, the total annual demand is more sensitive to building type or other indicator than the normalised profile. For example, 35 classes of building are considered when building up the annual demand but only 4 broader classes of buildings are needed to capture profile differences. Therefore, the annual demand is mapped into profile classes. The description of residential *thermal* profiles is described separately, in greater detail, in subsection 3.4.

For the residential *electric* demand the mapping of annual demand into profiles is particularly elegant. Grid forecasts use residential profile classes (see Section 4) corresponding to Standard and Economy-7 tariffs and the total annual demand can be mapped into these directly.

Table 1. An example calculation of annual thermal demand for residential buildings in one MLSOA. Table 1 below provides an example of the calculation of annual thermal energy demand of semi-detached houses that were built during 1901 – 1920 in the Harrogate 015 MLSOA.

Indicators		Benchmark	Demand
Houses in Harrogate 015	Average floor area	Thermal benchmark	Thermal Demand in Harrogate 015

semi-detached (1901 – 1920)	semi-detached (1901 – 1920)	semi-detached (1901 – 1920) Weather corrected using CIBSE TM46	semi-detached (1901 – 1920)
73 x	96 m ² x	188 kWh/m ²	= 1.3 GWh p.a.

Table 1. An example calculation of annual thermal demand for residential buildings in one MLSOA.

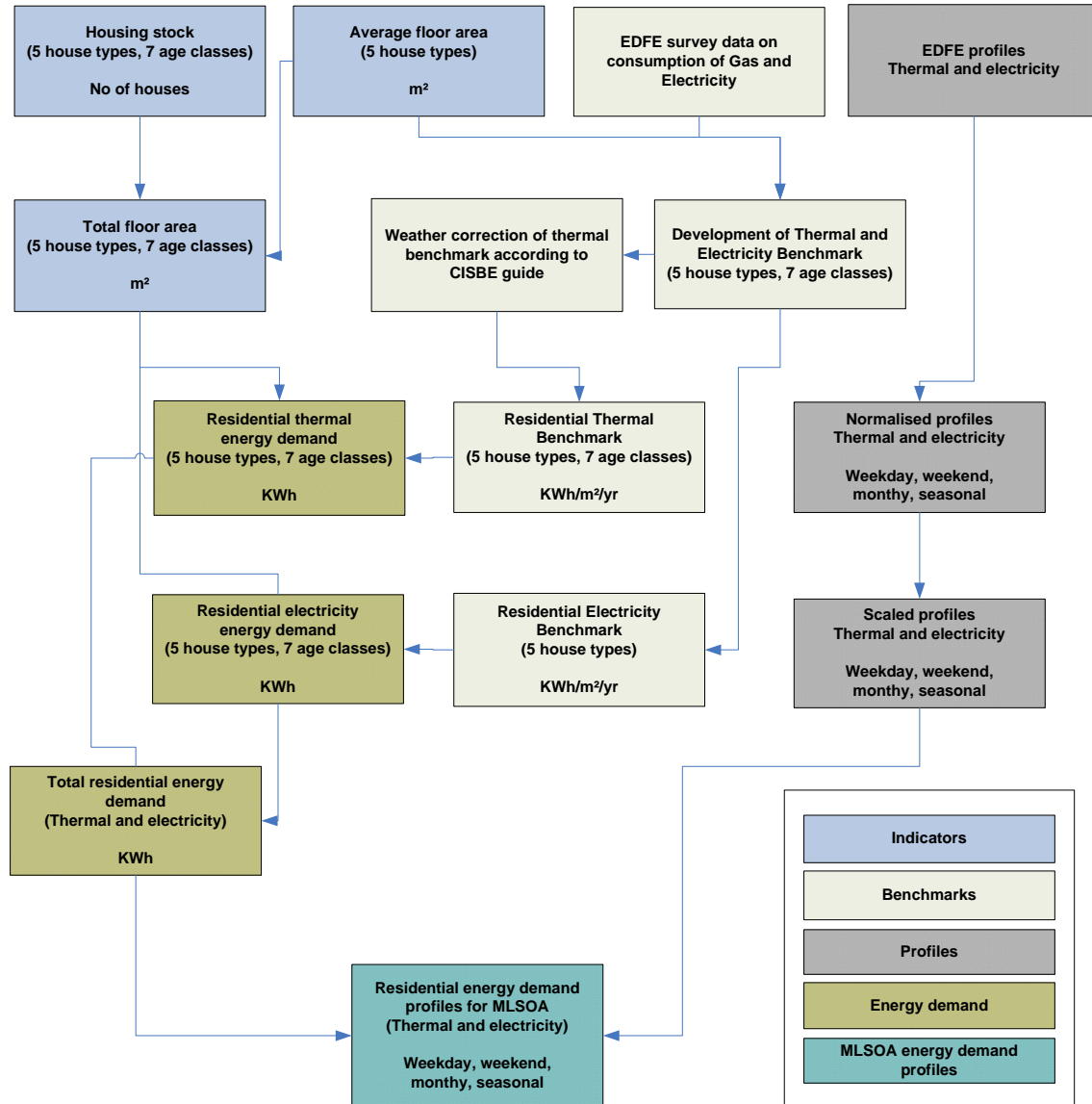


Figure 3. General methodology to calculate the residential energy demand

3.3. Non-residential Energy Demand

The non-residential energy demand (i.e. tertiary sectors including offices, hotels, schools, retail, etc.) is also calculated based on Equation 1. The detailed description of the methodology is described below.

The number of employees working in each business site is considered as the prime indicator of tertiary energy demand. This information is collected from the Marketsafe database

described further in Section 4. This data set also contains information on the business activity of the registered company site using a UK SIC (Standard Industry Code) code. The approximately 900 5-digit SIC codes are mapped into 29 broader energy demand classes defined in CIBSE’s TM46 guide (CIBSE 2008).

The number of employees according to each site SIC code is mapped into a subtotal for each of the 29 energy demand classes. The number of employees subtotals are then converted into the total floor area for those classes - by multiplying with conversion factors which are collected from EDF and other sources of tertiary sector intelligence (the conversion factors are described in greater detail in Section 4).

Tertiary indicator restoration: In the revised, *extension*, method an extra step has been developed to estimate the employee number indicator data when this is missing. As later sections will discuss, a significant number of *limited* companies omit this data. The restoration method, described in Appendix 2, estimates the missing data from nearby sites of the same business activity. If there are an insufficient number of indicator data points in same MLSOA to obtain a useful estimate, similar company sites at the whole district level are analysed.

The electricity and thermal benchmarks for 29 tertiary sectors are given by CIBSE’s TM46 guide (CIBSE, 2008). These benchmarks (both electric and thermal) are weather compensated by regional degree-days in the same way as the residential thermal demand.

The tertiary thermal and electric demand are distributed over the year using Profile data. The profile data sets are assembled from BDEW gas and electric utility profiles and from EDF tertiary profiles developed for designing CHP systems. The profile sets are described further in Section 4.

Figure 4 below gives an example of a tertiary sector annual demand calculation for the Harrogate 015 MLSOA .

Marketsafe Company SICs			
Publishing of books and music			
Cargo handling and travel agencies			
Post and telecommunications			
Banking and finance			
Insurance and pension funding			
Broking and fund management			
Real estate activities			
Renting of self-use equipment			
Computer and related activities			
Research and development			
Public administration activities			
Other service activities			
International organisations and bodies			

Indicator:	Indicator	Benchmark	Thermal Demand
Employees	Floor Area conversion	TM46 Thermal benchmark,	Harrogate015
<i>General Offices</i>	<i>General Offices</i>	<i>General Offices</i>	<i>General Offices</i>
2269 employees	23.0 m ² /employee	95 kWh/m ²	5.0 GWh p.a.

Figure 4. Example calculation of Office Thermal Demand for a Harrogate MLSOA

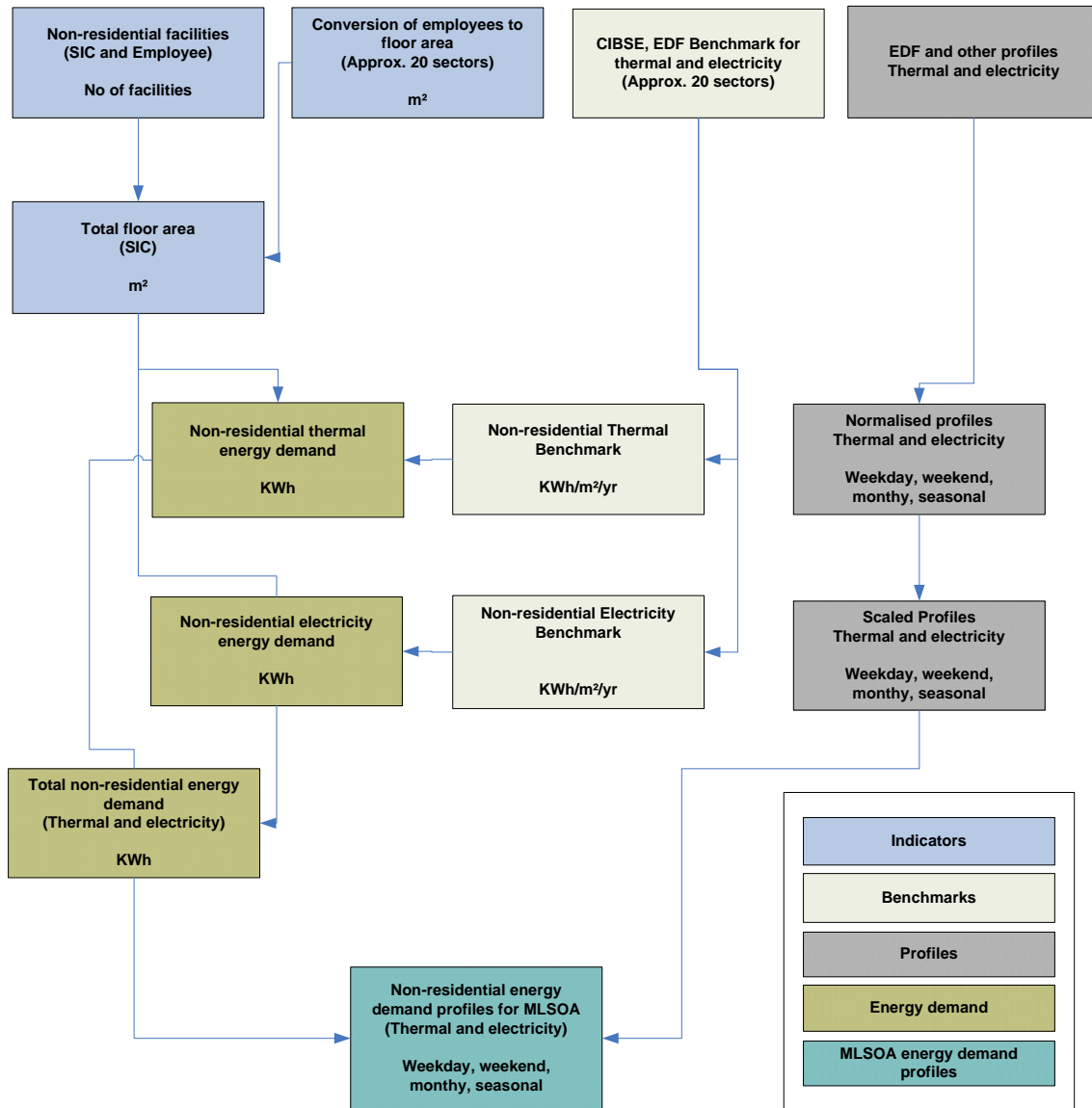


Figure 5. Methodology for tertiary energy demand

3.4. Modelling Temporal Residential Thermal Demand

A two level model is used to distribute the annual demand over a year. First, an energy *signature* is applied to distribute the demand over each day of the year. The model used here was developed by Geiger and Hellwig (2002) and can also be referred to as a single-variant model as it relates the mean daily thermal load to the mean outdoor temperature. In a second step, a black-box model approach is used to distribute the daily demand into hourly profiles. The profiles consists of a temperature-dependent statistic standardised hourly demand for different building types.

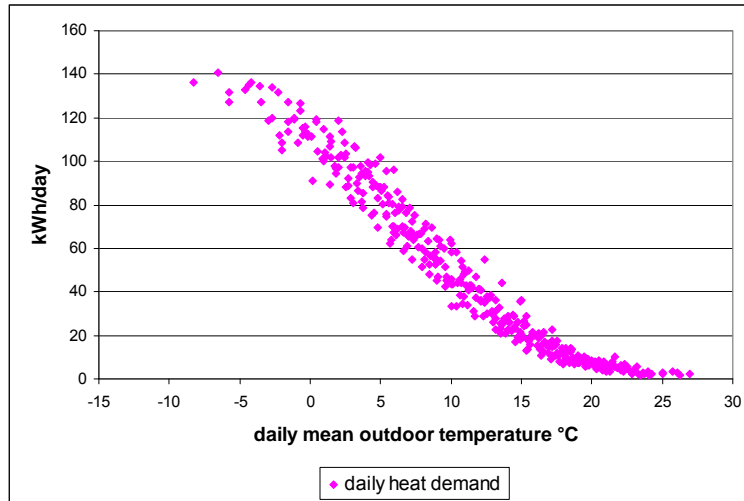


Figure 6: De-normalised energy signature model for individual households, source Koch 2010

Daily Thermal Demand

The sigmoid function (energy signature) is a result of research at the TU Munich and was further specified by BGW (2005). It is regarded as representative for current practice in the German gas market (KEMA 2009). Only few gas supply companies use other profiles than the one described here (ibid. 2009). In the German gas market, supply companies are obliged to apply an estimation for non-metered customers which have a maximum power consumption of 500 kW and a maximum annual gas consumption of 1.5 mil. kWh (GasNZV1). The level of precision of such a methodology to estimate the future gas consumption is obviously of high economic relevance for gas supply companies. (Eichlseder 2008) tested the transferability of the method to the Austrian market introducing the sigmoid function to be applied for the load prediction. In the assessment (Eichlseder 2008) points out two possible strategies to verify the results. On the one hand a bottom-up comparison with measured data is proposed which essentially rebuilds the energy signature with measured data of individual sites. For the residential sector in Austria 26 annual measurements were used with a total of 9625 usable daily values. In addition a top-down assessment was proposed using data from more than one hundred thousand gas customers. While both approaches showed a good match of measured data and predicted energy use it must be noted that with both possible approaches to test the reliability of the model's prediction past measured data was used. Depending on the purpose of the modelling therefore the question of which temperature data-set (e.g. TRY) is used for the load prediction becomes highly relevant as it includes an uncertainty that can not be excluded. Obviously, however, this is true for any modelling approach as even physical building models are limited by the prediction of weather conditions.

In the proposed signature model and load profiles, Geiger and Hellwig (2002) and Hellwig (2003) argue that above a size of 15 individual users (i.e. households) the confidence level of the energy signature improves substantially so that this level of aggregation could be termed a collective in the sense of the study. This was found to be consistent with prior studies (Grohmann 2000) conducted at the TU Munich. In the course of the data evaluation

¹ The „Verordnung über den Zugang zu Gasversorgungsnetzen, Gasnetzzugangsverordnung (GasNZV)“ is the German law regulating the access to gas networks

conducted by Geiger and Hellwig (2002), therefore, only measurements from a collective of more than 20 individual households are included in the residential sector.

In the study more than 20 collective measurements each containing over 20 individual households were used that were distributed over the whole of Germany to avoid specific socio economic or regional characteristics. Climate data of the Deutscher Wetterdienst was used.

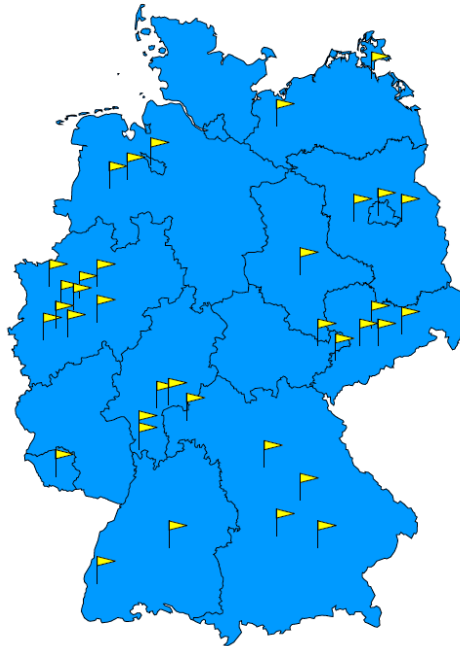


Figure 7: Distribution of all data sources used for the study of Geiger (2002) and Hellwig (2003) (note: these contain also non-residential measurement points)

As a starting point parameters used in the steady state calculation of residential heat demand were included to arrive at reasonable assumptions on the shape of the curve and namely the dependency of the heat demand on the outdoor temperature, as depicted in Figure 8. In their development, the profiles for different sectors were checked against the gas consumption data of nine energy utilities mains supply and resulted in an error of slightly above 10% in eight cases demonstrating that the various sectors were well represented and the aggregation of the different zones was consistent with the real values for the supply network.

The daily demand sigmoid function takes a generalised form for all buildings in a temperate climate, following the general argument of Hellwig (2003). The ISO standard equations for heat transfer through transmission and ventilation establish the approximately linear temperature dependence of the heat demand.

Heat transfer through transmission

$$Q_{tr} = H_{tr,adj} (\theta_{int,set,H} - \theta_e) t$$

$H_{tr,adj}$	total transmission heat transfer coefficient of the zone
$\theta_{int,set,H}$	set temperature for the zone
θ_e	outdoor temperature
t	time

Heat transfer through ventilation

$$Q_{ve} = H_{ve,adj} (\theta_{int,set,H} - \theta_e) t$$

$H_{ve,adj}$ total ventilation transfer coefficient
 $\theta_{int,set,H}$ set temperature for the zone
 θ_e outdoor temperature
 t time

The linear dependence of the heat demand on the outdoor temperature is represented by the yellow diagram in Figure 8. In addition, the almost-linear relationship of heat transfer through ventilation is included in the dotted blue line. Here based on prior studies (Geiger, Rouvel 1988) it is assumed that the ventilation rate decreases with lower outdoor temperatures. The green diagram represents a diminishing boiler efficiency with higher share of part load operation in summer. Finally the solar gains are included in the set of assumptions. The curving violet line is only considered to a degree, as heat gains will not be usable in summer and eventually can result in cooling loads.

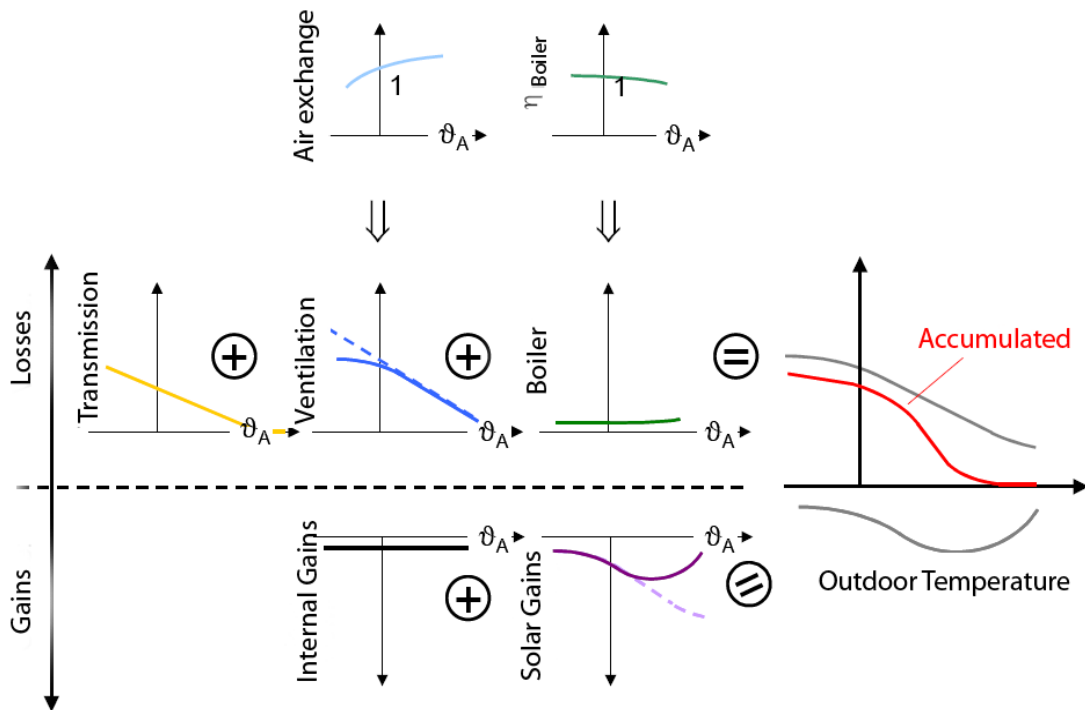


Figure 8: qualitative description of the dependence of heat demand from climatic influences, source: after Hellwig 2000

In the application of a prototype for a grey-box model for the energy demand in urban neighbourhoods, the comparison of steady state calculation and energy signature delivered similarly shaped distributions of a given annual demand (Koch 2010). Hence in the framework of the MACRO DE project the modelling relies on this tried and tested daily energy signature approach that is consistent with steady-state demand calculations.

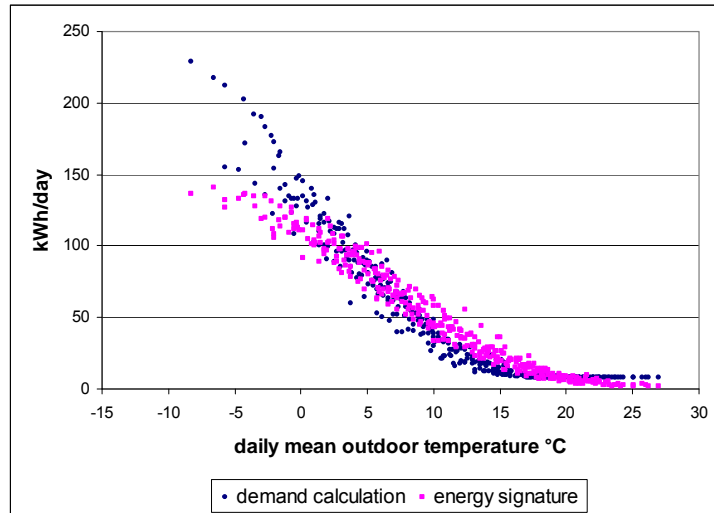


Figure 9: Comparison of calculated values and results from the energy signature model (Koch 2010)

Hourly demand profiles

So far the distribution model for the annual energy demand has described the approach for describing daily energy demand for different building types of the residential sector.

While the physical dependencies for the mean daily demand can be described in a qualitative manner as discussed above, the distribution over the hours of a day requires further characteristics in the demand description.

As already described by Hellwig (2003), the sampling at an hourly level tends to even out load peaks that exist particularly at a sub-hourly demand period (description of the load profile). Nevertheless, distinctive characteristics can be described with regard to the daily demand profile.

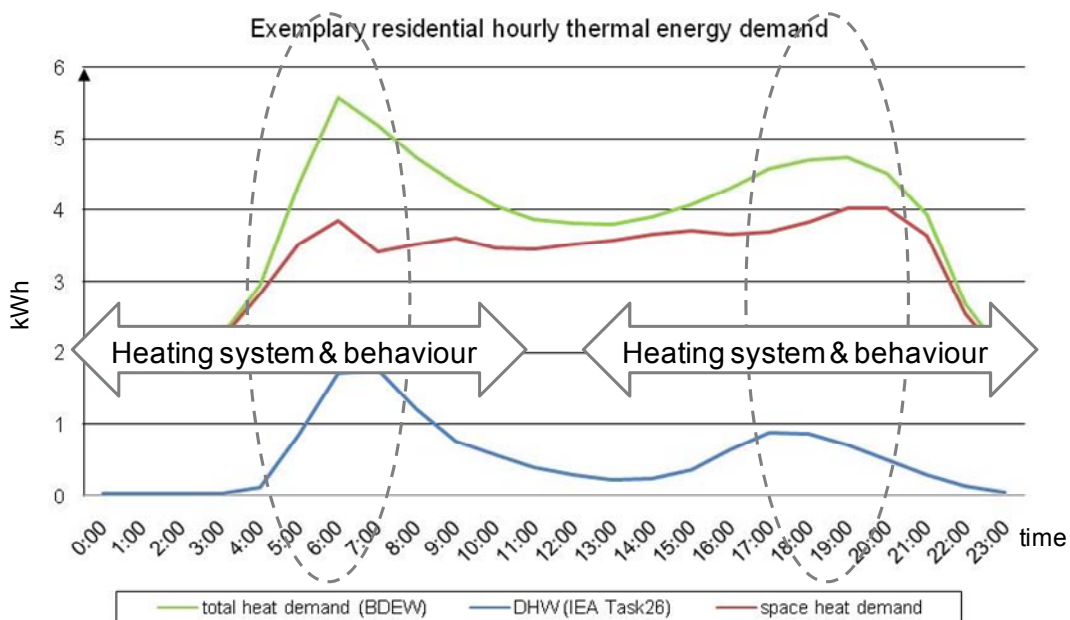


Figure 10: Composition of the thermal energy demand through the DHW demand and space heating requirements

Figure 10 shows a typical residential hourly profile at the aggregation scale used in the MACRO DE project. The profile shows a night time set back effect for the space heating demand. Morning and evening thermal usage is especially visible in the DHW profile. A similar approach is described by Jenkins, N., T. Sulka, et al. (2008) based on steady state calculations per time step using an overall loss coefficient for a building.

A common driver for morning and evening peaks are the necessity to heat up the space - in the morning after a period of night-time setback and in the evening as the outside temperatures drops. The heat demand for domestic hot water has a major impact especially in the peak loads as shown in Figure 10,.

Occupancy effects seem most directly visible in the DHW thermal demand, though are likely mediated by DHW system effects – e.g. whether heat transfer is instantaneous, buffered or scheduled. Space heating demand seems less consistently sensitive to occupancy. As internal heat gains from occupants are usually relatively low, this type of demand is determined, as described above, by building heating loss and system control settings.

Discussion of Drivers of Thermal Demand

As shown above, the distribution of energy demand over the year is strongly dependent on the mean outdoor temperature and the energy signature as described above can be explained using equations from ISO 13790 as a starting point. This point is reinforced by ASHRAE (ASHRAE, 2005):

“Extensive studies (Fels 1986; Katipamula et al. 1994; Kissock et al. 1993; Reddy et al. 1997) have clearly indicated that the outdoor dry-bulb temperature is the most important regressor variable, especially at monthly time scales but also at daily time scales.”

As the energy signature models generate characteristic temperature dependent distribution patterns that are supported by the general laws of physics, the general methodology is considered applicable to heating based climates (e.g. Germany and the UK). The generalised approach of energy signature models, as described by Geiger (2002) and Hellwig (2003), when applied to a particular application is dependent on a set of variables which is modified for different building types and age classes.

The differentiation between detached and multi-dwelling houses is explained by the varying relation between the volume and the external surface. The volume is included in the standard calculation of ventilation losses; the external surface determines the area to which heat transfer coefficients are applied. These two factors are, as explained above, the driving ones for the heat losses in addition to the temperature difference between indoor and outdoor temperature.

Finally, age classes defined as the share of old and new buildings will determine the steepness of the energy signature. BGW (2005) describes this share as a linear interpolation between the two individual curves proposed by Geiger (2002).

The generalised approach with its main dependence on outside temperature leads us to conclude that the shape of the energy signature function is similar for generic building classes such as new and old, detached and multi-dwelling houses between the UK and Germany. While the difference in building types is expressed in the different national benchmarks the distribution based on physical behaviour is expected to be similar.

In addition to the mean outdoor temperature, in the latest developments of the energy signature approach sometimes wind speed is included as a secondary influence on the energy demand. While BGW (2005) in their application included the opportunity to use wind speed as a modification to the initial model parameters it seems impossible to link the model to reliable data on windspeed in various land use settings (e.g. different urban/rural morphologies) especially as dedicated measurements of wind speed data are often located at airports or in open settings.

Hourly demand drivers

Whilst the hourly thermal profiles also depend on the mean outdoor temperature, on the orientation of transparent building parts and on the thermal performance of the building fabric, the main dependence (in both the UK and in Germany) is on heating control settings, such as night-time setback, and on DHW usage aspects (Woods, Riley et al., 2005) that are common to both countries. In practice, both countries contain a mix of basic (rotary on/off) and modern heating (with temperature set back and daily programme) control systems.

Throughout the process described above, the residential sector’s demand was used as a basis for discussing the various influencing factors. Here it can be said that different influences can be observed at different scales. This holds true for both the temporal scale as well as for the scale of the number of households aggregated into one load curve.

User	Building	Indoor temperature	Comfort needs Part heating
		Air exchange rate	Manual ventilation System operation Lifestyle
		Internal / solar gains	Applications Shadowing
	Heating system	Conversion	Characteristic curve Night time set back Operation
		Distribution	Hydraulic adjustment
		Ventilation	Operation Volume
	Domestic hot water (DHW)	Temperature	Temperature level User profile
		DHW usage	Comfort need Equipment

Figure 11: Parameters influencing the thermal energy demand related to user behaviour (after Richter 2002)

The influence of user behaviour on thermal demand can be subdivided into 1) effects via the building including the air exchange rate and the indoor temperature, 2) the operation of the heating system that plays a role when determining the total heat demand and finally 3) the domestic hot water (DHW) usage (Figure 11).

Regarding the impact of individual factors, and especially the building related factors, the EN 15603 standard describes numerous variables ranked according to their relevance and the distribution of the influence – as listed in Table 2 below.

Variable	Standard deviation		Distribution
	Calculated energy rating	Tailored rating	
Airflow rate from infiltration	0%	50%	log normal
Airflow rate from ventilation system	0%	10%	log normal
Area	2%	2%	log normal
Thermal transmittance (U-value)	10%	10%	log normal
System efficiency	5%	5%	log normal for x and 1-x
Internal temperature	0	1 K	normal distribution
Utilisation time	0%	25%	log normal
Volume	3%	3%	log normal
Depth, height	1%	1%	log normal
Electricity use (recovered as internal heat gains)	0%	10%	log normal
Frame factor (fraction of frame area in a window)	5%	5%	log normal for x and 1-x
Length	1%	1%	log normal
Linear thermal transmittance (ϕ)	10%	10%	log normal
Number of occupants	0%	10%	log normal
Shaded fraction, shading factor	5%	5%	log normal for x and 1-x
Thickness	5%	5%	log normal
Absorption coefficient	5%	5%	log normal for x and 1-x
Emissivity	5%	5%	log normal for x and 1-x
Heating power increase per degree external temperature decrease	20%	20%	log normal
Orientation (of collecting area for solar radiation)	5 °	5 °	normal distribution
Perimeter	2%	2%	log normal
Slope (of collecting area for solar radiation)	5 °	5 °	normal distribution
Thermal capacity	25%	25%	log normal

Table 2. EN 15603 standard ranked description of factors influencing thermal energy demand

The most influential factors are the air flow rate from infiltration and ventilation, the area, the thermal transmittance, the system efficiency and the internal temperature. This description is consistent with the general calculation approach described above. Apart from the indoor temperature which is assumed to follow a normal distribution in its variation the values are distributed over large number of cases via a logarithmic normal distribution (see Figure 12). This argues in favour of using a benchmark to represent the energy demand of building types and types of uses.

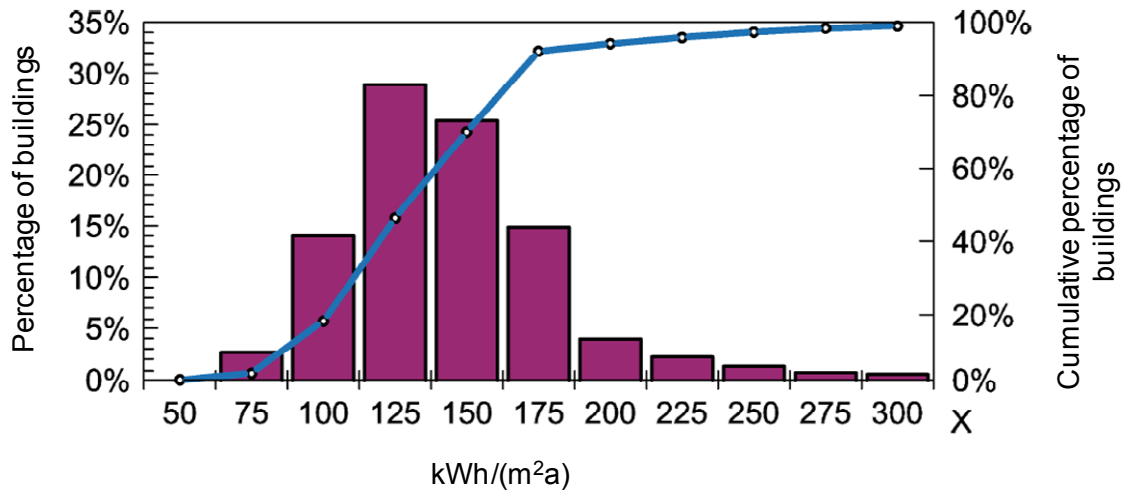


Figure 12: Sum of influencing factors and related specific energy demand for residential buildings as a log normal distribution (source: EN 15603)

Measurement campaigns such as the validation phase of the Passivhaus Projektierungspaket (Passive House Institute 2002) were used to estimate the minimal size of sample required to obtain a log normal distribution.

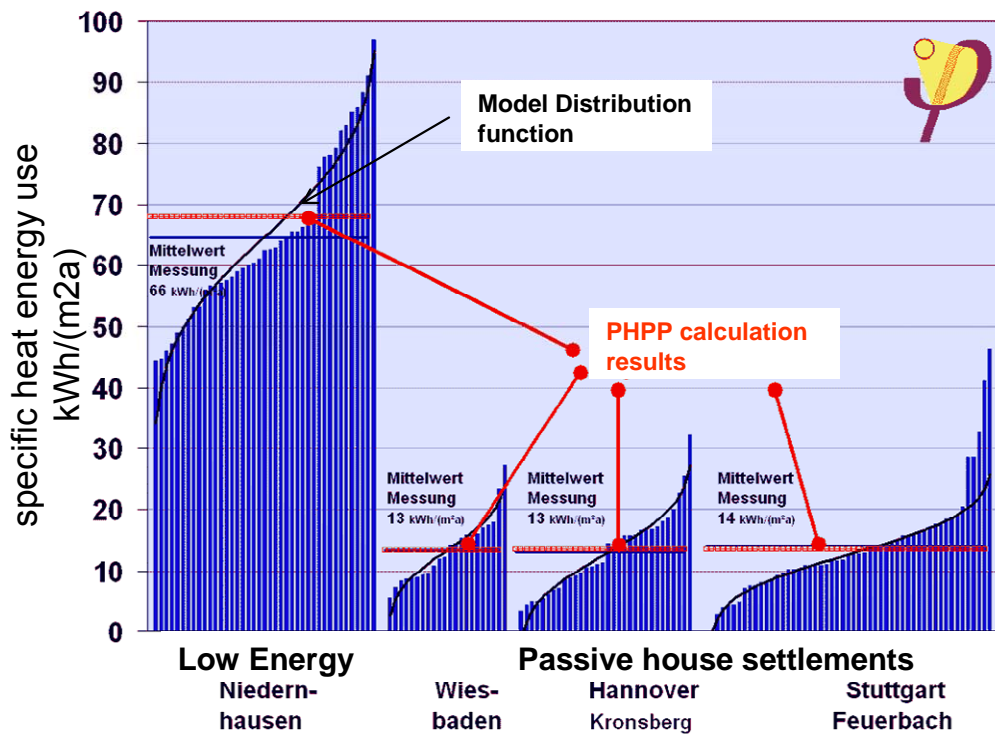


Figure 13. Distribution of specific energy demand across low energy buildings.

Example demand measurements from a German project conducted by EIFER showed that the tendency can already be seen using 51 buildings of similar types in the existing building stock. In addition the demand estimation is applied only to the scale of MISOAs and therefore not to units smaller than 5000 inhabitants.

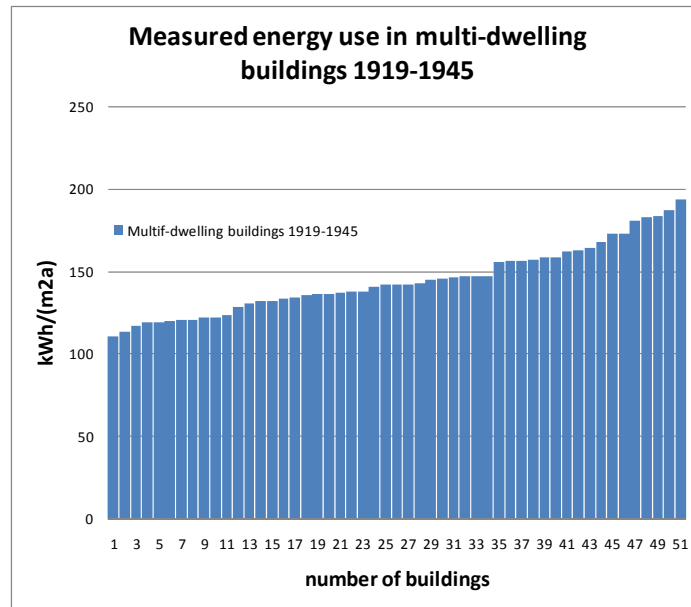


Figure 14: Distribution of specific energy demand of 51 multi dwelling buildings

The general argumentation used to illustrate distributional effects, illustrated in Figure 12, does not fully cover influences emerging from the general composition of households and the household income. While these social classifications are assumed to play a role in the individual household's energy use pattern their assessment would require exhaustive collection of additional data. To date the resulting influence seems not answered in a homogeneous manner in the scientific community. Often counterbalancing facts are described such as a lesser performance of buildings of lower income households in combination with a higher need to save energy and thus reduce costs (see Schломann, Gruber, et al. 2004). Santamouris, Kapsis, et al. (2007) arrive at similar findings, yet it must be noted that assessments of the impact of user behaviour in their explanatory power remain tightly linked to their national or regional context and the time of the assessment. Next to general possibly cultural expressions of energy use also daily routines as working hours can be expected to play a role in the energy use pattern. Here, however, the occupancy is not expected to be represented in individual load curves as strongly as it is the case for electricity profiles because heating system control strategies can be scheduled independently or as a function of the indoor temperature.

As a conclusion, the inclusion of hourly drivers in the current application remains limited to a black box type model. Therefore the modifications remain limited to the measurement of new specific profiles. Further work on specifying the impact of individual characteristics therefore seems most promising in the differentiation of domestic hot water (DHW) use even though this would require a separation of the DHW load and the load component for space heating (see Figure 10). In addition the separation could also be reflected in the sigmoid function as DHW use is represented as a constant use over the year.

3.5. Industrial Excess Heat

A three-step approach is used to calculate the industrial waste heat (or industrial *excess heat* that more accurately describes the available waste heat but that will be used synonymously).

1. Indicator data = employees per company. At first, all industrial companies of a certain area (e.g. MLSOA) are considered as potential heat suppliers. Their numbers of employees, the corresponding SIC-codes and the location or GPS-coordinates are taken from a commercial or statistical data base, in this case either Marketsafe or Geoplan. These will be called indicator data hence.

This list of companies will be reduced to only relevant industry sectors or processes for industrial excess heat. These are, for example, the heavy industries, some chemical processes, or paper industries. The selection will be made using the SIC codes.

Table 3 shows some sample rows from the Geoplan data to give an idea of what the data looks like. The Marketsafe data provide similar information.

Name of company	SIC	Location	Numbers of employees
Goldsmiths	52489	430232, 455282	1500
Cargo Logistics (UK) Limited	63400	419500, 462800	6
Knaresborough Pool	92620	435316, 456682	40
North Riding Finance Limited	65239	431400, 453500	7
Bright Interiors Limited	52420	433900, 475500	12

Table 3: Data example from Geoplan

2. Benchmark data = energy demand per company. Secondly, the numbers of employees per company are multiplied with an energy demand benchmark for French industries, which comes from EDF. These benchmarks are given per NAF-code² and show the energy demands per employee per year (e.g. [kWh/employee/year]). After the conversion of the NAF-codes to the SIC-code, the multiplication with the indicator data leads to the total energy demand of a single company per year.

The resulting list will be cut off at a certain amount of annual energy demand which corresponds to the minimum energy usage needed to be considered as a supplier of industrial excess heat. The exact limit is yet to be determined - it will depend on the process temperature and therefore on the SIC-codes, as well as the reliability and the availability.

An example of the conversion from NAF to SIC code is shown in Table 4 with additional information of the ISIC-, NACE- and SIC-codes and a short description.

ISIC	NACE	NAF	SIC	TITLES
A	A	A	01	Agriculture, Hunting and Forestry
-	AA	AA	010	Agriculture, Hunting and Forestry
1	1	1	01000	Agriculture, Hunting and Related Service Activities
111	111	011A	01110	Growing of Cereals and other commercial crops
112	112	011C	01120	Growing of Vegetables, Horticultural Specialities and Nursery Products

Table 4: Conversion of NAF-codes to SIC, ISIC and NACE with explanation

² NAF-codes (Nomenclature des Activités Françaises) are French industry codes that are similar to SIC. For the calculation the NAF- will be converted into SIC-codes.

3. Benchmark data = Excess heat per company. Finally, the resulting numbers are multiplied with a second benchmark, which provides per SIC code the potential of excess heat. This benchmark, provided by University of Bath, results from a detailed analysis of the processes in place in each sector. In particular, the various process temperatures are referenced (e.g. 1000°C for aluminium processing industry), as well as the various exhaust heat flows (e.g. heat flow at 100°C from the smelter). Then ratios are calculated that relate the exhaust heat flows to heat demand (e.g. exhaust heat from aluminium processing corresponds to 15% of heat demand). This ratio, representing the ratio of usable excess heat to heat demand, ranges between 0 and 1. Table 5 provides examples (lower and higher bands) of excess heat ratios

Industry Sector	Excess heat ratio	Temperature of excess heat [°C]
Aluminium	0.1 – 0.15	100
Iron and Steel: Coke ovens	0.13 – 0.26	1100
Glass	0.1 – 0.2	550

Table 5: Excess heat ratio and temperature of the excess heat per sector and SIC-code

Excess heat for distributed energy

The multiplication of rows from table 3 with the correspondent rows from table 4 and 5 will lead to the total amount of industrial excess heat per company. The aggregation will be based on the geographical areas that will be found in work package 2.



Figure 15. Multiplication process for industrial excess heat

3.6. Space cooling for the commercial sector

CIBSE TM46 energy benchmarks do not separate out cooling demand from electric demand. CIBSE Guide F describes detailed end use benchmarks for offices, banks and agencies and hotels that include cooling. The cooling benchmarks do depend on building ventilation or installed air-conditioning, but this type of information is not available at present.

Cooling profiles are available for offices, retail and hotel buildings. We do not have separate DECC consumption data for cooling to validate cooling demand calculations. Given the patchy nature of this data, it would require a distinct effort to calculate reliable cooling demand.

3.7. Industrial electricity

CIBSE TM46 benchmarks do not describe industrial energy demands. CIBSE Guide F describes building energy use for space heating and other (maybe electric) uses, as well as process energy in kWh/m² per year. As described above, EDF also has a database of energy benchmarks for industrial sectors in France in kWh/employee per year.

The registered company datasets are able to identify specific industries and provide indicator data on them. This forms part of the approach that would be used to estimate waste heat.

We currently do not have any temporal profiles for Industrial electricity demand. To calculate industrial *electric* demand would require finding reliable benchmarks (and profiles) with electricity demand broken out.

3.8. Working Assumptions

The project explored and categorised the assumptions inherent in the demand estimation method. They are tabulated below.

Category 0 - General Assumptions

No	Description	Category	Discussion
1	4 demand components are of interest: (residential, tertiary) x (thermal, electric)	General	These sectors contribute 38 per cent of final UK energy consumption (DUKES 2008)
2	can swap UK - GB	General	not treating Northern Ireland initially; NI consumption <3% of UK domestic energy (BRE)
3	industrial demand not of interest for demand side	General	Industrial sites are not potential DH customers
4	ignore climate change	General Thermal	Can apply weather compensation to benchmarks and re-calculate profiles; very little impact on demand zone creation
5	Demand analysed is the Gross potential	Purpose	technical, economic and availability filters and factors can be applied subsequently
6	ensemble profiles aren't peaky	Scale	diversity of consumers & demand level the profiles
7	Peak prediction has worst uncertainty	Statistics	Because there are few days with this temperature extreme

Category 1 – Energy Related Assumptions

No	Description	Category	Discussion
8	80% boiler efficiency for converting gas consumption to thermal production	Thermal	See Project assumptions agreed w/ ETI WP1
9	gas - thermal ratios	Thermal	UK services ratio: 0.84 (DECC Service sector update); UK domestic ratio: 0.85 (BRE Domestic energy fact file)

10	Parametric-statistical thermal model works for GB	Thermal Model	the model includes key dependencies on temperature and building class; hourly statistics capture common drivers such as DHW and night-time setback; the approach has already been extrapolated to Austria - see discussion on thermal modelling
11	DHW consumption is fairly constant on daily basis	Thermal Model	actually DHW is not explicitly modelled in our approach.
12	normal distbn of set points	Thermal Model	
13	log normal distbn of ventilation	Thermal Model	
14	Large part of thermal residential demand depends mainly on temperature	Thermal Model	State of the art BDEW method, also validated
15	Electric demand includes Economy 7 usage	Electrical	this is a significant component and source of hourly electric levelling until/unless it is superseded by other thermal supply

Category 3 – Assumptions for Validation

No	Description	Category	Discussion
16	CHP Ops is a good residential validation site	Validation	it has lots of old and newly built residential flats- that is of interest – see further validations
17	DECC energy consumption per MLSOAs	Validation	DECC guidance note: domestic consumption allocation is > 97.5% in majority of LAs
18	DH Losses not included	Validation	This is a supply-side parameter; we are calculating end user <u>demand</u>

Category 4 – Demand Type Related Assumptions

No	Description	Category	Discussion
19	MLSOAs residential demand shows large diversity	Residential	MLSOA has pop. Of typically 5000
20	EDFE residential thermal benchmark	Residential Thermal	UK weather corrected following CIBSE guideline for all UK regions; EDF validated customer tool
21	Residential housing stock in 2001 is considered as indicator data for residential thermal demand	Residential Thermal	Latest available housing stock data set at MLSOA level – can include annual 1% increase (BRE)
22	employee to surface conversions	Tertiary	see #24
23	tertiary demand depends on business activity	Tertiary	this is probably valid for electric; for thermal demand building type will also have an influence

24	Tertiary sector energy demand can be predicted by # employees	Tertiary	for the tertiary sector, personnel is the main business resource and there are typical working space requirements; exceptions could be schools, hotels, hospitals
25	tertiary similar across DE,FR GB	Tertiary	this is a reasonable initial assumption because of the complexity of the sector
26	Missing employee records for tertiary sectors can be estimated from regional or national average indicators	Tertiary indicator	sites with same industry code will have similar procedures and labour needs across large areas so are good estimators – this is a standard estimation approach

4. Demand Related Data Sets

4.1. Overview

		Residential		Tertiary	
		Thermal	Electrical	Thermal	Electrical
Indicators	Data Set	35 house types	2 elec contracts	#employees 900 SICs	
	Level	MLSOA	MLSOA	Post Code	
	Source	<i>EDF Energy</i>	<i>DECC</i>	<i>Creditsafe</i>	
Benchmarks	Data Set	>40 house types	annual demand estimated directly from indicators	29	
	Level	Region		Region	
	Source	<i>EDF Energy</i>		<i>TM46 (CIBSE)</i>	
Profiles (hourly)	Data Set	4 house types x 7 temp ranges	2 elec contracts	11 x 7 temp ranges	8
	Level	Region	Region	Region	Country
	Source	<i>BDEW + UK Weather data</i>	<i>EDF Energy</i>	<i>BDEW + UK Weather data</i>	<i>BDEW</i>

4.2. Indicators

EDF Energy: House types by MLSOA

EDF Energy uses detailed datasets on consumers as part of its customer research activities. From these datasets, detailed housing stock statistics were extracted by MLSOA to provide indicator data for this project. The indicators are categorised according to five housing types (detached, semi-detached, terraced, bungalow and flat) and seven age classes (before 1990, 1990 – 1920, 1921 – 1940, 1941 – 1960, 1961 – 1975, 1976 – 1990, after 1991).

DECC: Residential Electrical consumption by MLSOA

A significant differentiator of electrical consumption is the type of subscription tariff: Economy 7 or standard (Yohannis, 2008 and Hamidi, 2009). The total consumption per MLSOA according to these two types are available directly from DECC's compilation of electric consumption by MLSOA.

Creditsafe: employee number at registered UK companies sites.

Creditsafe Business solutions Limited³ offers credit rating related services and data on 4.4 million UK companies from all sectors. The data is gathered from information registered at Companies House, The Registry Trust and the London & Edinburgh Gazette. Data on the number of employees working at each company site is used as an indicator of tertiary energy demand. This data set also contains information on the business activity of the registered

³ For more information on Marketsafe data, please refer to the report "Comparison of Geoplan and Marketsafe data" prepared for the ETI.

company site using a UK SIC (Standard Industry Code) code. Approximately 900 5-digit SIC codes are mapped into 29 CIBSE TM46 energy demand benchmark classes.

Tertiary employee indicator conversion to floor area

EDF routinely performs market studies to understand its client base. Data to establish employee to built floor area ratios was derived from two separate studies on the UK tertiary sector. These used employment statistics from e.g. Eurostat and the Office of National Statistics and data on floor area from consultancies such as BASIC and BIPE. The table below summarises the ratios obtained.

Sector	conversion factor (m²/employee)
Tertiary	27
Offices	20-26
Retail	21-23
Hotel + Restaurant	24-31
Public Buildings	24
Education	22

Table 3. Tertiary sector built area to employee ratios

EDF Energy: Climate data

EDF Energy’s meteorology team provides weather data and scenarios for EDF Energy’s consumption forecasts. Regional degree day data are used for weather compensation of residential and tertiary energy demand benchmarks. Regional daily average temperatures are used directly in constructing profiles for residential and tertiary thermal demand.

4.3. Benchmarks

EDF Energy benchmarks from EDFE customer energy savings tool

The residential benchmarks for both thermal and electricity demand have been extracted from a survey carried out (about 9000 households surveyed in the London, South and West of England where EDF’s customer base is located) by EDF using a proprietary tool that can predict customer savings from energy efficiency measures. It includes detailed information on the housing types, number of bedrooms, construction ages, electricity and gas consumption, etc. The gas consumption is then aggregated for five housing types and seven age classes. Considering an average gas boiler efficiency of 80%, a total of 35 thermal benchmarks are derived. These benchmarks should differ according to the geographic location; therefore, weather adjustments to the benchmarks have been applied based on the CIBSE TM46 guidelines (CIBSE 2008).

CIBSE TM46 energy demand benchmarks (2008)

Electricity and thermal benchmarks for 29 sectors are collected from CIBSE TM46. These benchmarks are the key to calculating the tertiary annual energy demand.

4.4. Profiles

As previously described, annual demand is distributed over days and hours using *normalised profiles*. Besides the description below, detail on profile sets is given in Appendix 3.

One of the challenges in the project, and a main focus of the extension of work on the development of the demand estimation methodology, was the gathering of detailed and representative profile sets. For example, UK gas transporters are obliged to perform daily load estimation predictions (for non-metered customers) but do not currently perform this calculation at hourly level (xoserve, 2009). As a result, reliable UK hourly thermal profiles are relatively difficult to obtain.

BDEW gas profiles

Because of the lack of a utility-grade hourly gas load model in the UK, we turned to a German gas grid forecasting method used by the BDEW that does provide a detailed hourly gas consumption profile. This method is largely determined by building physics and typical thermal systems and occupant behaviour - and its main dependence is on climate data – as described above in Section 3.4. By substituting UK climate data, we can describe the many of the detailed features of UK gas demand – as explored in the validation described in Section 5.2. Further details on the BDEW method for gas profiles for the residential and tertiary sectors are described in Appendix 3 – the modelling approach is described in Section 3.4.

EDF Energy Forecasting Residential Electric Profiles

EDF Energy produces detailed forecasts of non daily metered electric consumption for its (6 million) residential customers. EDF Energy forecasts distinguish between 2 distinct types of consumption patterns: due to standard and Economy 7 subscriptions and use a profile for each. The estimated load curve in each area then depends on the proportion of each type of consumption.

EDF Sustainable Solutions Profiles

The project started with a set of profiles from EDF Energy's Sustainable Solutions group. These were developed by EDF for bidding for and designing CHP systems. They were not considered sufficiently detailed and validated to rely on for residential demand but do provide partial coverage of UK tertiary demand.

Four hourly profile data sets are available for the hotel, retail, schools and offices tertiary sectors for both thermal and electricity demand. This data set is normalised and aggregated to derive daily (typical weekday and weekend), monthly and seasonal profiles.

BDEW tertiary electric profiles

The BDEW also provides sets of electric profiles according to sector (8 tertiary and 3 agricultural) for non daily metered tertiary consumers. These can be used to complement the tertiary profile data sets from EDF Sustainable Solutions where the difference between patterns of commercial electric consumption in the UK and Germany are not expected to be very different.

5. Validating Demand Calculations

5.1. Annual Demand Calculation for Harrogate

The methodology has been tested on Harrogate 015 MLSOA, which is one of the 21 MLSOAs in Harrogate within the region of Yorkshire and Humber in the North of England (Figure 16). According to the Census data in 2001, it has a population of 8252, with 3952 households in an area of approximately 214 hectares (DECC, 2007).

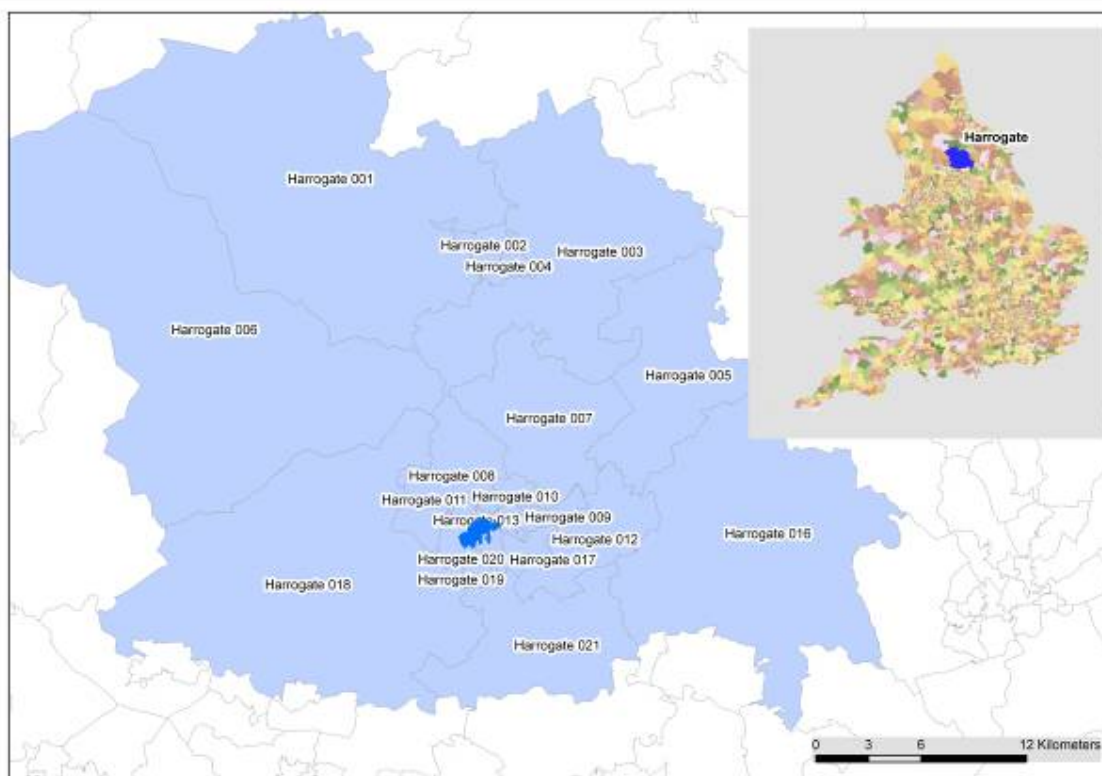


Figure 16. Description of the trial area (top right figure shows the location of Harrogate in regard to England, whereas the main figure illustrates its MLSOAs and the highlighted blue area is Harrogate 015)

A wide range of data sets are needed to carry out the trial methodology. These include indicators, benchmarks as well as profile data sets for the residential and tertiary sectors. These are described in greater detail in Section 4.

The calculated total annual thermal and electricity energy demand in Harrogate 015 is about 107 GWh and 59 GWh respectively. Figure 17 shows the share of this energy demand by sector.

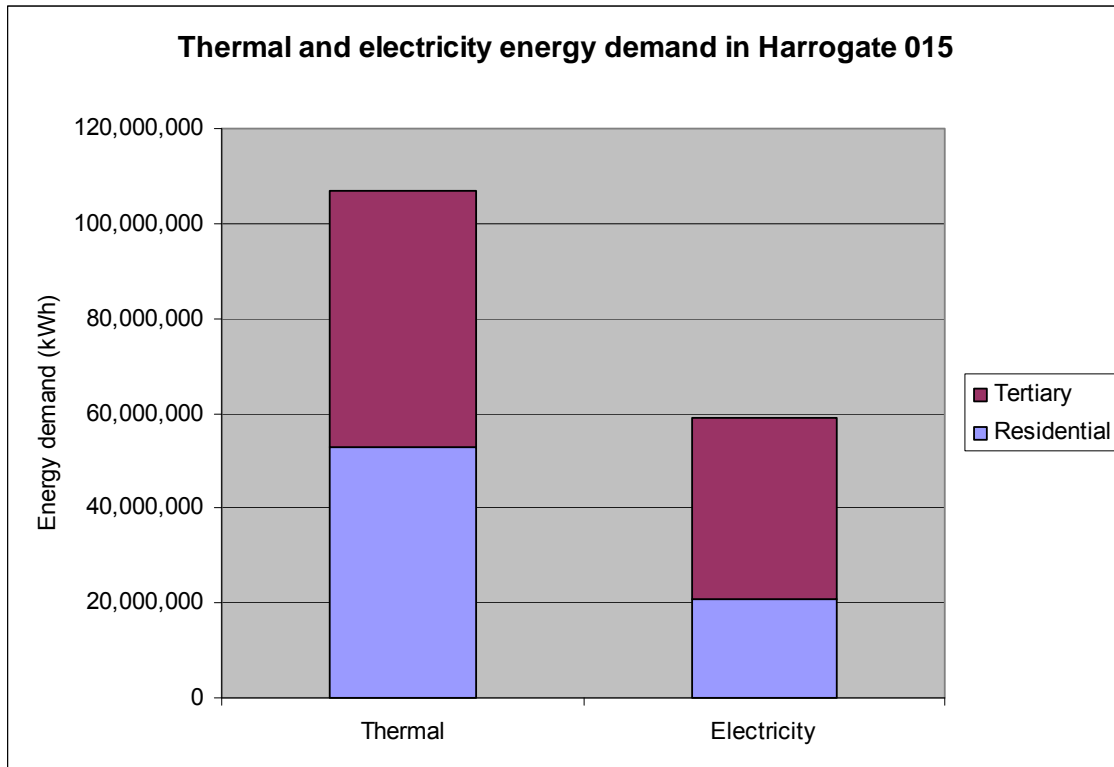


Figure 17. Calculated annual thermal and electrical demand in Harrogate MLSOA 015

For the statistical analysis of the results, the residential thermal demand calculation was performed on all 21 Harrogate MLSOAs. The resulting error distribution is given in Section 6.4 and the spatial distribution of the energy demand is shown in Figure 18.

Results of tertiary indicator restoration

The restoration of employee indicator data, described in Appendix 2, was checked by applying the method to a number of Harrogate MLSOAs. The MLSOAs were selected to consist of tertiary sites rather than industrial so that the predicted demand could be compared with DECC data for MLSOA energy consumption. The selection criteria were: a large number of commercial sites, in a densely populated area with a relatively low commercial energy consumption per site. Five MLSOAs satisfied these criteria and the restoration results for these are presented below in Table 4.

MLSOA	% missing indicator data	% missing after restoration
HG 015	59%	16%
HG 009	47%	5%
HG 010	47%	3%
HG 014	48%	5%
HG 019	77%	15%

Table 4. Results of restoring tertiary employee indicator data

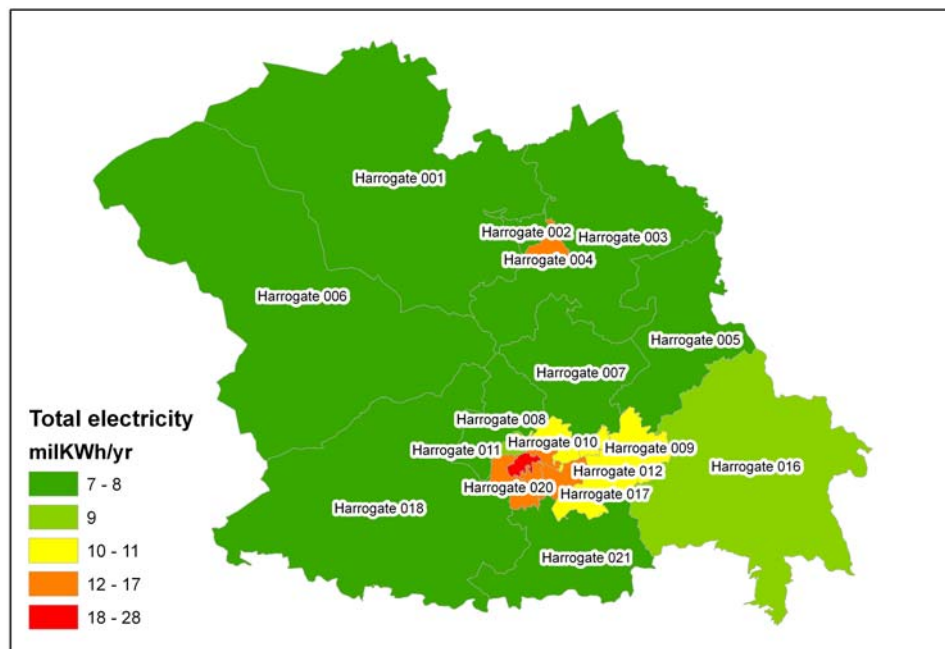
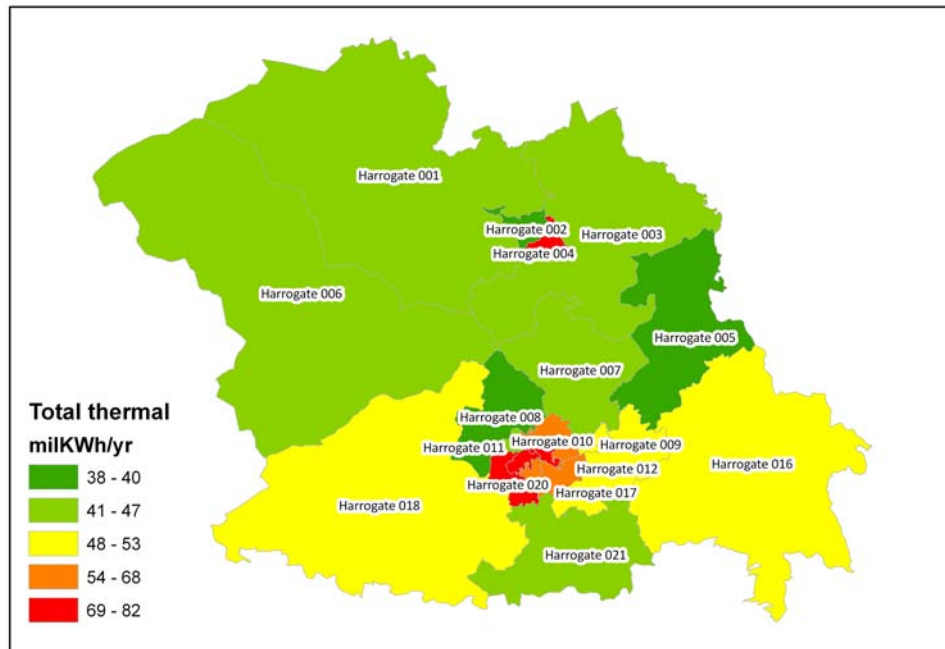


Figure 18. Total thermal and electricity energy demand in Harrogate

5.2. Calculations for “CHP Ops” Cogeneration and District Heating Site

For the validations of the proposed method, almost two years of data were available from a district heating system with a CHP unit, referred to as “CHP Ops”. The site will not be identified to protect customer data. The district heating system consists of 12 residential multi-dwelling buildings with about 500 apartments in total. These buildings were constructed between the 1960s and 2005, but exterior insulation has been added to the 60s’

and 70s' buildings. Most of the apartments are considered to be social housing. The residential sector data has been aggregated to provide anonymity.

The tertiary sector consists of a primary school, a nursery and a leisure pool with a fitness centre. These customers have been measured individually and this data has been available for the validation. Calculations will only be shown for the whole tertiary sector to protect customer privacy.

The size of the district heating system is less than one tenth of the size of an MLSOA (see Figure 19). The total energy consumption of the district heating network is about the same ratio compared to the consumption of an MLSOA. Thus, in comparison to a Macro DE Zone the demand of this network is between 1/50 and 1/100 of the zonal demand.

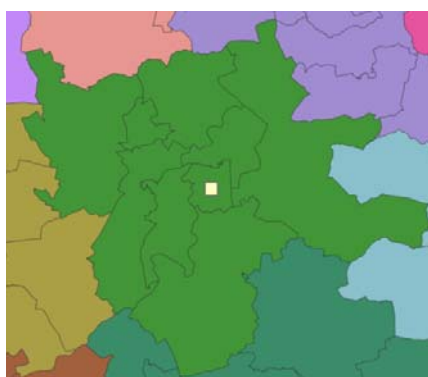


Figure 19: Size of the area of the district heating network of CHP Ops (white square) compared to individual MLSOAs (black lines) or a Macro DE Zone (green area)

The measured data was taken in two intervals, the first one ranging from February, 2nd of 2008 to January, 27th of 2009, while the second part was measured between July, 5th of 2009 and July, 6th of 2010. The data consisted of measurements taken every ten minutes for the whole district heating system, the residential buildings in total and for each tertiary building.

Thus, calculations could be done for the validation of the annual, daily and hourly demand. The annual demand for the period of 2008/09 was predicted to be 6.7 GWh, while the real, loss corrected values showed a demand of 5.4 GWh. This is an overestimation of 26 %. The results for the residential demand was much closer with an overestimation of only 17 %, but the tertiary sector has been predicted to be more than 50 % higher than the real measurements. The data can be seen in Table 5.

	Predicted	Measured loss-corrected	Error
Residential	4.7 GWh	4.1 GWh	+ 17 %
Tertiary	2.0 GWh	1.3 GWh	+ 54 %
Total estimated	6.7 GWh	5.4 GWh	+ 26 %

Table 5: Prediction and measured (loss-corrected) data for CHP Operations for the period of 2008/2009 with error of prediction

The daily demand calculations were renormalised on the measured annual demand data in order to isolate the daily level prediction error. In the prediction method the annual demand is distributed over the year according to the outside daily mean temperature, which has

been measured at the CHP Ops site. Different parameters are used for each type of buildings.

Shown here are the figures for the whole district heating network: The energy signature, the annual duration curve and annual load curve.

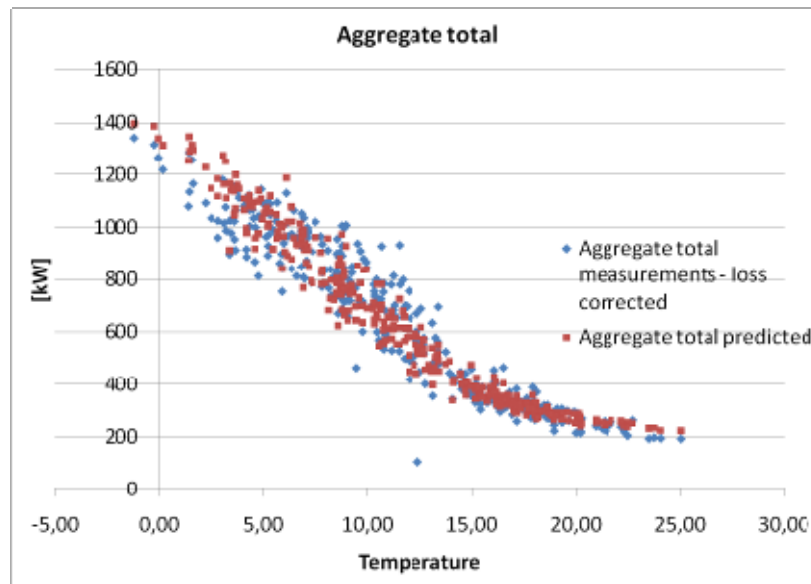


Figure 20: Energy Signature of the aggregated total measurements (blue) and the total predicted (red) for different daily mean temperatures

The energy signature is used to show the correlation of the outside temperature and the consumed heating demand. The heat consumption is showing the s-shaped curve which is used in the prediction method. The scattering occurs due to the insulation effects of the buildings, thus the daily consumption does not only depend on today's temperature, but also on the temperatures of the days before.

The prediction follows the measured data very closely as can be seen in Figure 20, although the scatter is larger in the measured data.

The annual duration curve is usually used to estimate the size of heating units. It show the daily demand sorted in descending order. Figure 21 shows the annual duration curve for the measured data of the district heating system (blue curve) and the method's prediction (red curve). These lines follow each other with a small overestimation at the peak days and an underestimation in the intermediate days (between day 100 and day 200).

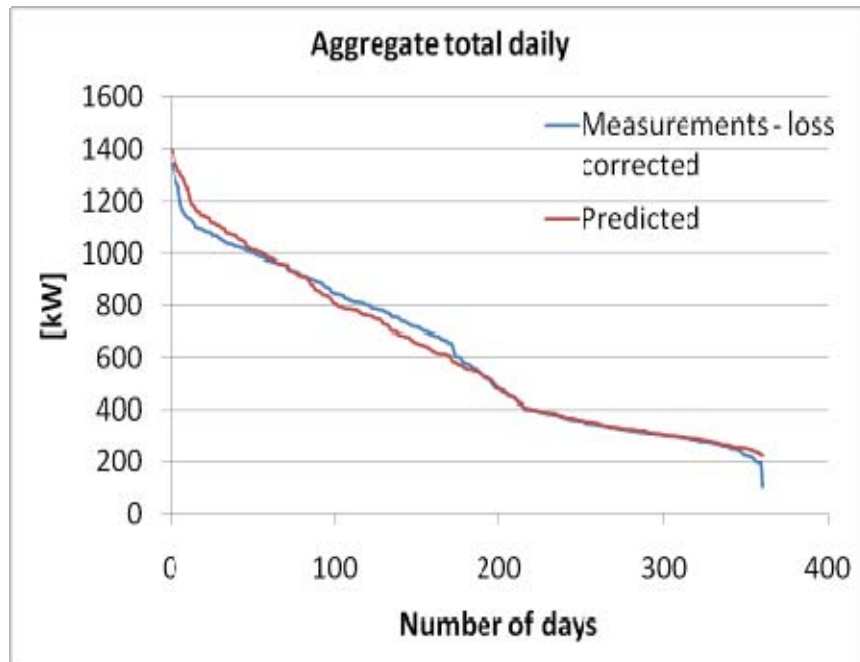
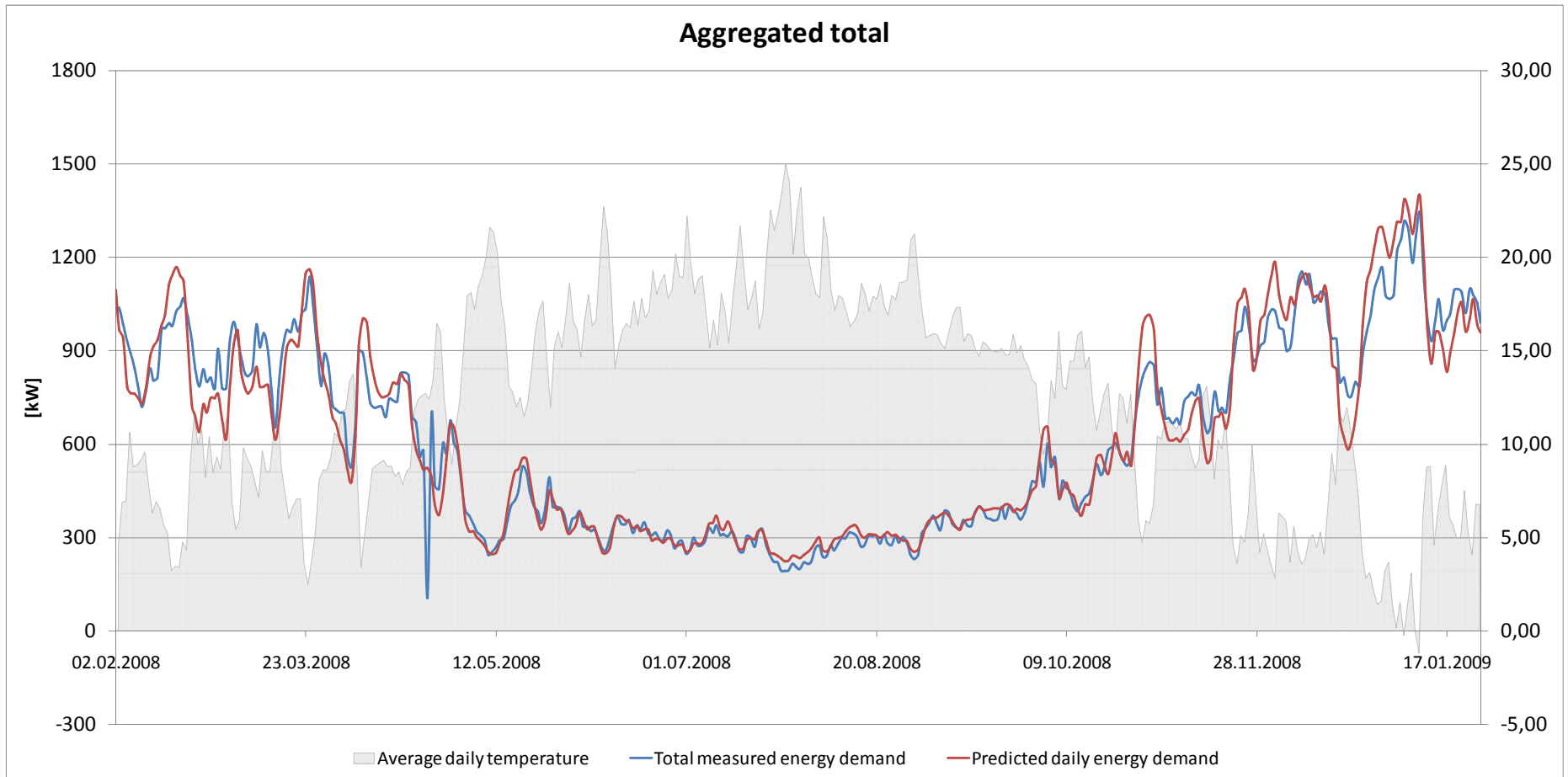


Figure 21: Annual duration curve for the measured (blue) and predicted (red) load curves

The next step in the analysis can be seen in Figure 22. It shows the same values as in Figure 20 and Figure 21, but this time in chronological order. The graph also shows the temperature curve of the period of 2008 and 2009 (in grey) measured at the site. The dependency of both load curves on the temperature can be seen directly. The method shows a good prediction in general, but there are prediction discrepancies when the temperature changes rapidly.

Breaking down the data into hourly level for the same period of time, the graph is getting confusing. The points are so close by each other that a distinction of the curves and a conclusion about the accuracy of the prediction can hardly be done (upper part of Figure 23). The two graphs at the lower end of Figure 23 are showing two extracted weeks from the hourly load curve. The first one is one week of July. Here the prediction is quite close to the measured data during the working days. There is a slip of the peak time in the hour for weekend. For a winter week (lower right part of Figure 23) the result changes. It can be seen that the consumption during the night is lower than anticipated. Therefore there is an overestimation of the morning peak, while the evening peak is underestimated. This effect is once more most significant during the weekend.



**Figure 22: Annual load curve for the measured (blue) and predicted (red) data.
The mean daily temperature (green) is shown as well**

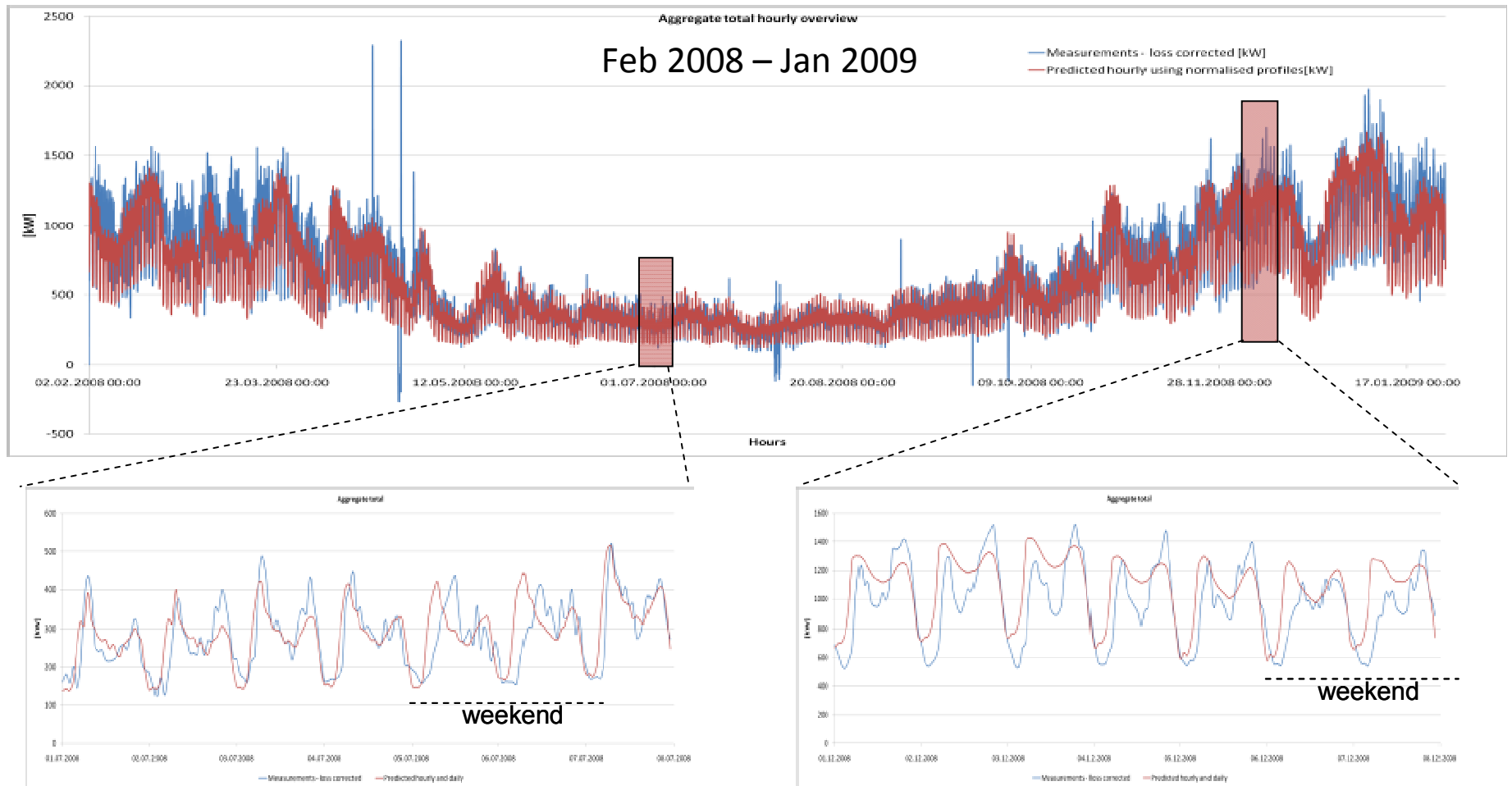


Figure 23: Hourly load curves for Feb 2008 to Jan 2009. The measured curve is shown in blue, while the prediction is red (graph at the top). The two downer graphs are showing two extraction of one week each of the annual load curves. The left one has been taken in summer, the right curve is showing a winter week,

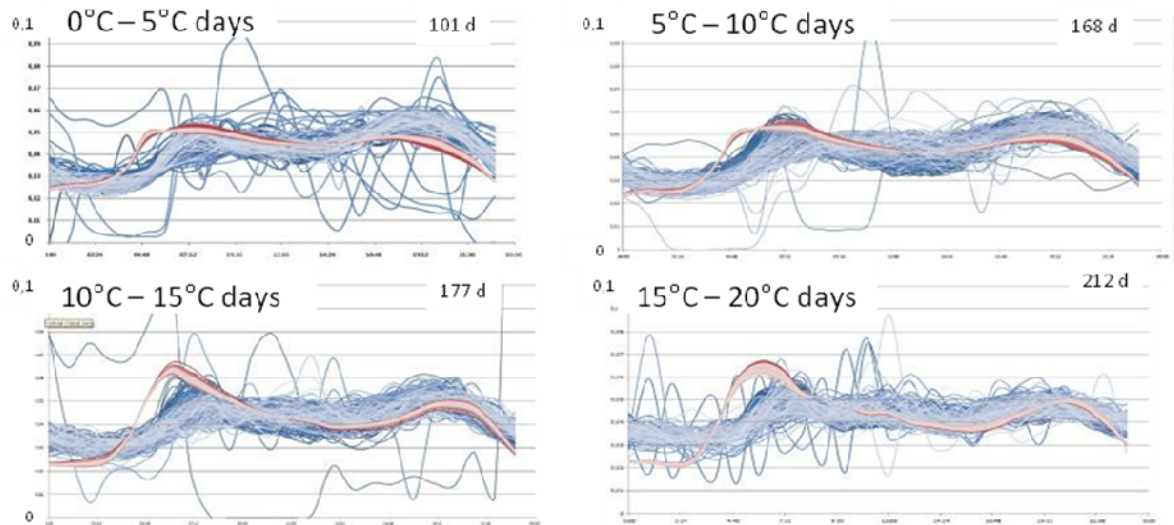


Figure 24: Comparison of measured data (blue) and the prediction (red) for days within an interval five degree, starting at 0°C

The differences on the prediction of the morning peak and the evening peak can be analysed more clearly in the four parts of Figure 24. For these graphs the days within a five degree interval have been normalised and put on top of each other, showing the bands of blue lines. Errors in the measurement data have not been deleted. The same days' predictions have been put into the graphs as the red-coloured bands. The number of days within one five degree interval is represented in each graphs upper right corner.

During the warmer days (10 – 15 °C and 15 – 20 °C, two lower graphs of Figure 24) an underestimate during night time and an overestimate during the morning hours can be seen. On the other hand, the colder days (0- 5 °C and 5 – 10 °C, two upper graphs of Figure 24), show that the morning peak is at the same height of the hourly demand distribution over the day, but not at the same time. The modelled morning peak is about one hour early.

On balance, the model predicts many of the temporal features and the pattern of the district heating network load well. It is arguable whether, for example, a 1 hour shift in the precise morning load would have a significant impact on a heat supply system with thermal storage. The overall result is a promising sign that the method can be used for other parts of the UK.

6. Statistical Analysis

6.1. Introduction and Approach

The statistical analysis part of the Trial aims to assess the levels of uncertainty in the development of domestic and non-domestic temporal energy demand. It exercises the energy demand calculation on a number of MLSOAs and on a district heating site to gauge the effectiveness of the data and method that will be used to compute energy demand across the UK.

Two analysis approaches have been developed. A first, “bottom-up” approach, considers the variation and errors inherent in the indicator and benchmark variables that contribute to the energy demand calculations. Error propagation techniques are then used to estimate the resulting energy demand uncertainty.

A second, “top-down”, analysis compares the computed energy demands for Harrogate MLSOAs, residential and tertiary, thermal and electric, with MLSOA electric and gas consumption values from the UK Dept. of Energy and Climate Change (DECC, 2007). The distribution of discrepancies between these 2 figures gives another perspective on the computed energy demand uncertainty.

The statistical analysis of profile prediction errors looks at the differences between predicted and measured loads over a whole year of data at the “CHP Ops” district heating site. The prediction errors are decomposed into their annual, daily and hourly components.

6.2. Assumptions

The statistical analysis relies heavily on the Central Limit Theorem (CLT) of probability – according to which the mean of a sufficiently large number of independent random variables⁴ will approximate a Normal distribution. The CLT approximation is very likely to hold for aggregated energy demand at the MLSOA level because of the large number of independent energy contributions. To a significant extent, the CLT can also be invoked at the level of the individual variables that make up the demand calculations, where these quantities result from many underlying random components and especially in the absence of strong evidence for another distribution.

The importance of this approximation is that it enables the use of analytic expressions for e.g. error propagation.

There may, however, be exceptions to the Gaussian distribution approximation. Some groups of demand contributions contain distinct classes of sub-components. Examples could include residential building groups (e.g. semi-detached 1901-1920) in which distinct building performance classes will exist, e.g. unrefurbished and refurbished – this could give rise to a multi-modal distribution instead. As another example, the tertiary sector energy

⁴ The Central Limit Theorem conditions for the underlying random variables include: independence as well as finite mean and variance. The requirement for identical distributions can be relaxed according to Lyapunov’s condition.

benchmarks have been divided into usefully distinct classes but employee/floor area conversion ratios are only available at larger grouping levels and these ratios could have multi-modal error distributions.

There are also some variables that exhibit correlation. Thermal demand and electrical demand, for instance, could both be related to energy efficiency measures or operating hours.

6.3. “Bottom-Up Analysis” of Likely Errors

All reported errors are assumed to be random variables unless described as systematic.

Tertiary Sector:

Employees

The accuracy of employee data from the MarketSafe registered companies database is inconsistent. Where available, it is given to the nearest employee – though some of the values for the larger companies may be the results of taking a mid value in a range [MarketSafe]. Given that the average number of employees per company in Harrogate 015 is 5 to the nearest employee, we estimate an accuracy of 1 in 5 i.e. an average error of +-10%. In very many of the limited company records, however, the employee value is missing (92% of Ltd. company have missing employee data for Harrogate 015 MLSOA compared to only 4% missing for non Ltd. companies). For Harrogate 015 MLSOA, this gave a likely employee number under-estimate of approx 60% compared to the smaller random variations. The missing employee statistics are described in a separate report on the registered company databases (Murshed, 2010). After applying the restoration method described in Appendix 1, the systematic underestimate of employees can be reduced to about 10% (see Table 4).

Likely error in data:

+ - 10% relative std. dev.

approx 60% systematic employee underestimate across Harrogate 015 (according to Marketsafe approx 40% across UK). After restoration this underestimate is reduced to approx. 10%.

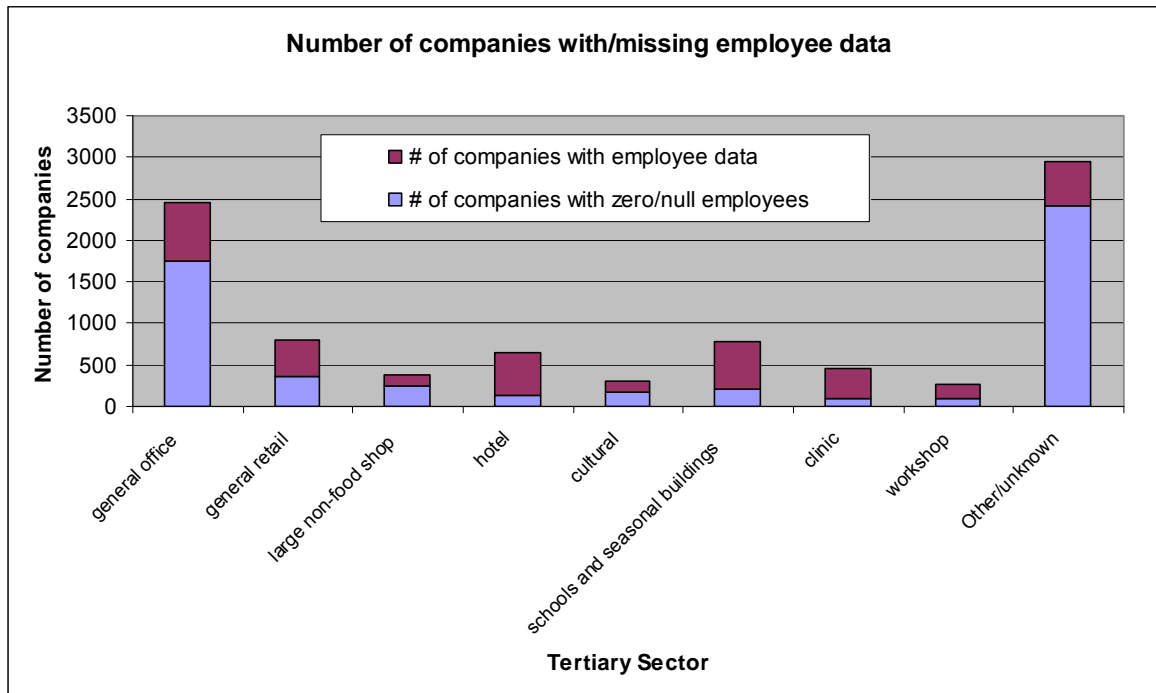


Figure 25. Analysis of Energy Classification of Companies with missing employee data for Harrogate

Energy Classification

The mapping and classification of SIC codes into CIBSE TM46 energy benchmark classes is highly non-linear and it is difficult to quantify the uncertainty inherent in the process. Therefore the current error estimates are based on expert analysis from working with the mapping process. This mapping is also one of the areas where the method is subject to ongoing refinement. On the one hand, there are approximately 900 SIC codes to map into just 29 distinct energy benchmarks so the mapping could be performed with good resolution. On the other hand, SIC codes classify company activity rather than building type. For example, a chemical industry company in Harrogate could have a variety of buildings, including administrative, warehousing as well chemical factories. This effect will tend to underestimate the contribution of generic building types such as offices and storage.

Likely error in data (from expert analysis):

- +/- 20% relative std. dev. from misclassification errors
- 5 - 10% systematic underestimate of generic building types.

Conversion from employees to area

The area per employee conversion factors rely on tertiary sector intelligence for employee numbers and building surface area. EDF has conducted studies of this kind but much of the available data is at large sector levels such as “hotels and restaurants”. Other tertiary sector groups are missing and have to be estimated from the total tertiary statistics. As a result, conversion values become representative when sufficiently aggregated but could be in error for individual sub sectors. Without the necessary detailed tertiary sector intelligence it is difficult to estimate the size of the likely sub-sector error. The quantity provided, therefore, is based on expert analysis.

Likely error in data (from expert analysis):

- +/- 75% relative std. dev.

Energy Demand Benchmarks

Benchmark building consumption data is available from reliable sources such as CIBSE (CIBSE, 2008). It is harder, however, to obtain data on the natural variability of building consumption. The EL-Tertiary report has measured the electric consumption of samples of tertiary buildings in order to gauge the potential for energy conservation. The BRE's Non-Domestic Building Energy Fact File (BRE, 1998) provides example measured distributions of total energy for offices and shops respectively. The variances estimated using these data sources are provided in Table 6 below.

Energy Classification	Thermal Demand		Electric Demand	
	relative Std.Dev. (%)	comment	relative Std.Dev. (%)	comment
general office	36%	BRE study 64 offices	88%	from EL-Tertiary EU 51 sample quartiles, skewed distbn: 84 +72 -29
high street agency	45%	<i>estimated from mean std. dev.</i>	60%	<i>estimated from mean std. dev.</i>
general retail	54%	BRE study 63 shops	56%	from EL-Tertiary EU 10 sample quartiles, much higher skewed distbn: 503 +140 -239
large non-food shop	45%	<i>estimated from mean std. dev..</i>	60%	<i>estimated from mean std. dev.</i>
small food shop	45%	<i>estimated from mean std. dev.</i>	60%	<i>estimated from mean std. dev.</i>
large food shop	45%	<i>estimated from mean std. dev.</i>	60%	<i>estimated from mean std. dev.</i>
restaurant	45%	<i>estimated from mean std. dev.</i>	60%	<i>estimated from mean std. dev.</i>
bar, pub ..	45%	<i>estimated from mean std. dev.</i>	60%	<i>estimated from mean std. dev.</i>
hotel	45%	<i>estimated from mean std. dev.</i>	49%	from EL-Tertiary EU 10 sample quartiles, lower skewed distbn: 70 +38 -9
cultural	45%	<i>estimated from mean std. dev.</i>	60%	<i>estimated from mean std. dev.</i>
entertainment halls	45%	<i>estimated from mean std. dev.</i>	60%	<i>estimated from mean std. dev.</i>
swimming pools	45%	<i>estimated from mean std. dev.</i>	60%	<i>estimated from mean std. dev.</i>
fitness and health centre	45%	<i>estimated from mean std. dev.</i>	60%	<i>estimated from mean std. dev.</i>
dry sports and leisure facility	45%	<i>estimated from mean std. dev.</i>	60%	<i>estimated from mean std. dev.</i>
covered car park	45%	<i>estimated from mean std. dev.</i>	60%	<i>estimated from mean std. dev.</i>
public building light usage	45%	<i>estimated from mean std. dev.</i>	60%	<i>estimated from mean std. dev.</i>
schools and seasonal buildings	45%	<i>estimated from mean std. dev.</i>	71%	from EL-Tertiary EU 26 sample quartiles, slightly skewed distbn: 23 +14 -8
university campus	45%	<i>estimated from mean std. dev.</i>	60%	<i>estimated from mean std. dev.</i>
clinic	45%	<i>estimated from mean std. dev.</i>	60%	<i>estimated from mean std. dev.</i>
hospital	45%	<i>estimated from mean std. dev.</i>	42%	from EL-Tertiary EU only 5 sample quartiles, lower slightly skewed distbn: 35 +14 -6
long term residential	45%	<i>estimated from mean std. dev.</i>	51%	from EL-Tertiary EU only 4 elderly homes sample quartiles, higher slightly skewed distbn: 108 +33 -41
general accommodation	45%	<i>estimated from mean std. dev.</i>	60%	<i>estimated from mean std. dev.</i>

emergency services	45%	estimated from mean std. dev.	60%	estimated from mean std. dev.
laboratory	45%	estimated from mean std. dev.	60%	estimated from mean std. dev.
public waiting	45%	estimated from mean std. dev.	60%	estimated from mean std. dev.
terminal	45%	estimated from mean std. dev.	60%	estimated from mean std. dev.
workshop	45%	estimated from mean std. dev.	60%	estimated from mean std. dev.
storage facility	45%	estimated from mean std. dev.	60%	estimated from mean std. dev.
cold storage	45%	estimated from mean std. dev.	60%	estimated from mean std. dev.

Table 6. The Estimated Likely Error in Tertiary Sector Demand Benchmarks.

Residential Sector

Number of houses

The housing number data comes from an EDF database of number of buildings by type and age and was aggregated from full postcode level up to MLSOA level. It should therefore be accurate to within 1-2 buildings. The average number of houses per class in Harrogate 015 MLSOA is 120 so the likely error is less than 1 or 2 in 120 or +-1%

Likely error in data:

+/- 1% relative std. dev.

Energy Demand Benchmarks

Residential benchmark values for thermal demand were derived from an EDF customer energy efficiency calculation tool. The tool's model was calibrated with data from surveys. Consumption predictions include the effects of occupant behaviour and number of rooms but, as detailed statistics on these parameters per MLSOA were not available to us, demand values were estimated as the mean. The effects of occupant behaviour and number of rooms can however be expected to contribute to the variance of results. The likely error for each of the 35 residential building classes was estimated from the Variance calculated over the calculated range of output values from tool's predictions.

Likely error in data:

ranges from approximately +/- 15% relative std. dev. on newer houses to approximately +/- 40% on pre-1900 buildings (as shown in Table 7 below)

DETACHED		SEMI-DETACHED		TERRACED		BUNGALOW		FLAT	
Age	Rel Std. Dev.	Age	Rel Std. Dev.	Age	Rel Std. Dev.	Age	Rel Std. Dev.	Age	Rel Std. Dev.
before 1900	50%	before 1900	41%	before 1900	33%	before 1900	42%	before 1900	39%
1900 - 1929	32%	1900 - 1929	25%	1900 - 1929	23%	1900 - 1929	0%	1900 - 1929	32%
1930 - 1949	28%	1930 - 1949	22%	1930 - 1949	23%	1930 - 1949	23%	1930 - 1949	26%
1950 - 1966	22%	1950 - 1966	20%	1950 - 1966	23%	1950 - 1966	24%	1950 - 1966	18%
1967 - 1975	20%	1967 - 1975	21%	1967 - 1975	24%	1967 - 1975	20%	1967 - 1975	35%
1976 - 1990	17%	1976 - 1990	14%	1976 - 1990	20%	1976 - 1990	13%	1976 - 1990	27%
1991 -	21%	1991 -	16%	1991 -	22%	1991 -	0%	1991 -	32%

Table 7. Calculated relative standard deviations across the 35 residential building classes.

DECC MLSOA Electricity Consumption Data

The electricity consumption data per MLSOA from DECC is expected to be relatively reliable. Apparently (DECC, 2009), for most districts 97.5% of consumption could be correctly allocated to MLSOAs. Across the UK, all but 6 districts could correctly allocate 95% of electric meters.

Likely error in data:

less than +/- 5% of MLSOA electric consumption.

Error Propagation Analysis

Error propagation techniques can be used to estimate the variation in a variable that is a function of several other independent random variables. For the case where the underlying random variables are Normally distributed, satisfactory analytic expressions have been derived. The more general case is often approached via Monte Carlo simulation.

The general energy demand calculation equation for the demand methodology can be characterised as

$$\text{Demand, } D = \sum_{i \text{ sectors}} \sum_{j \text{ sites}} (I_{ij} \times B_i) \quad (2)$$

where the indicators I_{ij} can vary per site (e.g. number of site employees) but the same benchmarks B_i are used within each sector i . These are treated as random variables with standard deviation σ_{Iij} and σ_{Bi} , respectively.

Using standard error propagation techniques (Gertsbakh,2003), it can be shown that the resulting variance in the demand is given by:

$$\sigma_D^2 = \sum_{i \text{ sectors}} \{ (\sigma_{Bi}^2 \sum_{j \text{ sites}} I_{ij}^2) + (B_i^2 \sum_{j \text{ sites}} \sigma_{Iij}^2) \}. \quad (3)$$

For the residential sector, where $I_j = 1$ and $\sigma_{I_j}^2 = 0$, the simplified expression becomes

$$\sigma_D^2 = \sum_{i \text{ sectors}} (J_i \sigma_{Bi}^2), \quad (4)$$

where J_i is the number of houses per building class.

Error Propagation Results

Residential Thermal Energy Demand

Equation 4 was used to propagate the residential sector component variances up to the Harrogate MLSOA 015 level. The major contribution to the variance in the residential thermal demand came from pre-1900 residential buildings. However, because there were over 3000 of these properties, averaging effects reduced the predicted error to +- 1%.

Tertiary Energy Demand

Equation 3 was used to propagate the tertiary sector component variances up to the Harrogate MLSOA 015 level. The predicted random error on tertiary thermal demand was 9%. The predicted random error on tertiary electric demand was 8%. These are both considerably lower than the uncertainty of the data making up the demand calculation because of the averaging effect of many companies.

Note that error propagation calculations are known to often underestimate the random error in the final result because of additional random variations or relations between the input variables (Gertsbakh, 2003).

6.4. "Top-Down" Harrogate MLSOA statistics

This aspect of the statistical analysis replaces the original validation step. It was realised that it is not so useful to validate the estimation of a result subject to uncertainty with a single, or even a few, reference values. If the results are within estimated error bounds, the computation is “validated” but it doesn’t inform us whether the outcome was lucky or repeatable. Much more interesting could be an outcome that doesn’t validate the calculation method – this would suggest that the original error estimation needs adjusting.

Having developed the demand calculation method, it was decided to spend a little more time and extend it over all 21 MLSOAs in Harrogate. This could provide a sample of demand calculations and thus perhaps some insight into their likely error distribution⁵.

The DECC database provides Domestic and Industrial/Commercial consumption of Electricity and Gas on an MLSOA basis. The DECC gas consumption data is multiplied by a typical gas boiler efficiency of 80% to give equivalent thermal demand. Not all heating systems use gas however, so the DECC values also need multiplying by a gas heating systems factor. EDF has strategic studies on the proportion of fuels used across the UK that suggests a national average value 0.86 across the UK.

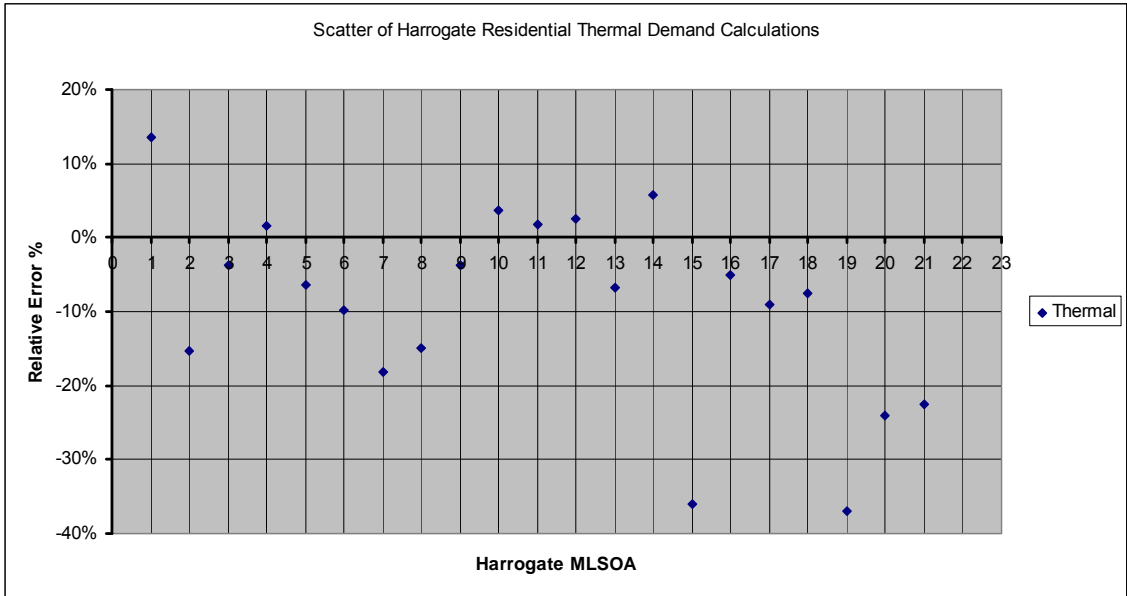
Using the BRE domestic energy fact file (BRE, 2001) data on the energy balance of the UK housing stock suggests a ratio between UK domestic gas consumption and useful thermal demand of 0.85 (see Appendix 5). Performing the same analysis on the UK tertiary sector using data from DECC’s service sector tables on energy consumption in the UK (DECC, 2009) gives a similar ratio of 0.84.

Unfortunately, these gas consumption to thermal demand conversion values can be significantly different in rural regions. A more responsive indicator is the DECC data on the ratio of gas meters to electric meters. The assumption here is that if a household has a gas meter then it is on the gas network and it will use gas for its heating and otherwise it will not. Having converted between consumption and demand values, the differences between demand calculations and DECC values are plotted below as scatter graphs.

Note that the DECC consumption values combined industrial with commercial consumption whereas our demand calculations for the tertiary sector did not include industry. As a result, the DECC values should be higher for MLSOAs with significant heavy industry. This was not expected to be the case for Harrogate 015 – one of the reasons for which it was originally chosen. The scatter results shown below now include the results (pink data points) after restoring the number of employees data on MLSOAs selected for their likelihood to have a low industry component.

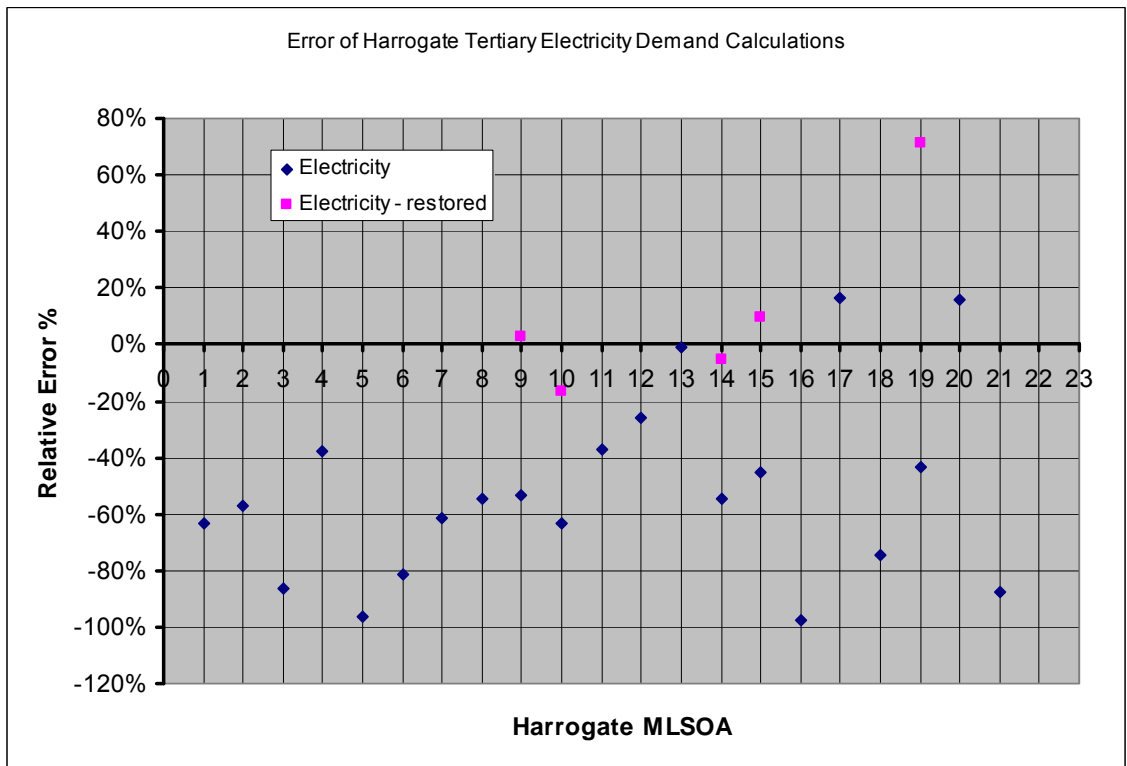
Residential thermal scatter results

⁵ In principle, the distribution of errors in demand calculations across MLSOAs need not be the same as the distribution of error in the calculation of a single MLSOA, though this assumption, related to *ergodicity*, is often used in statistics.

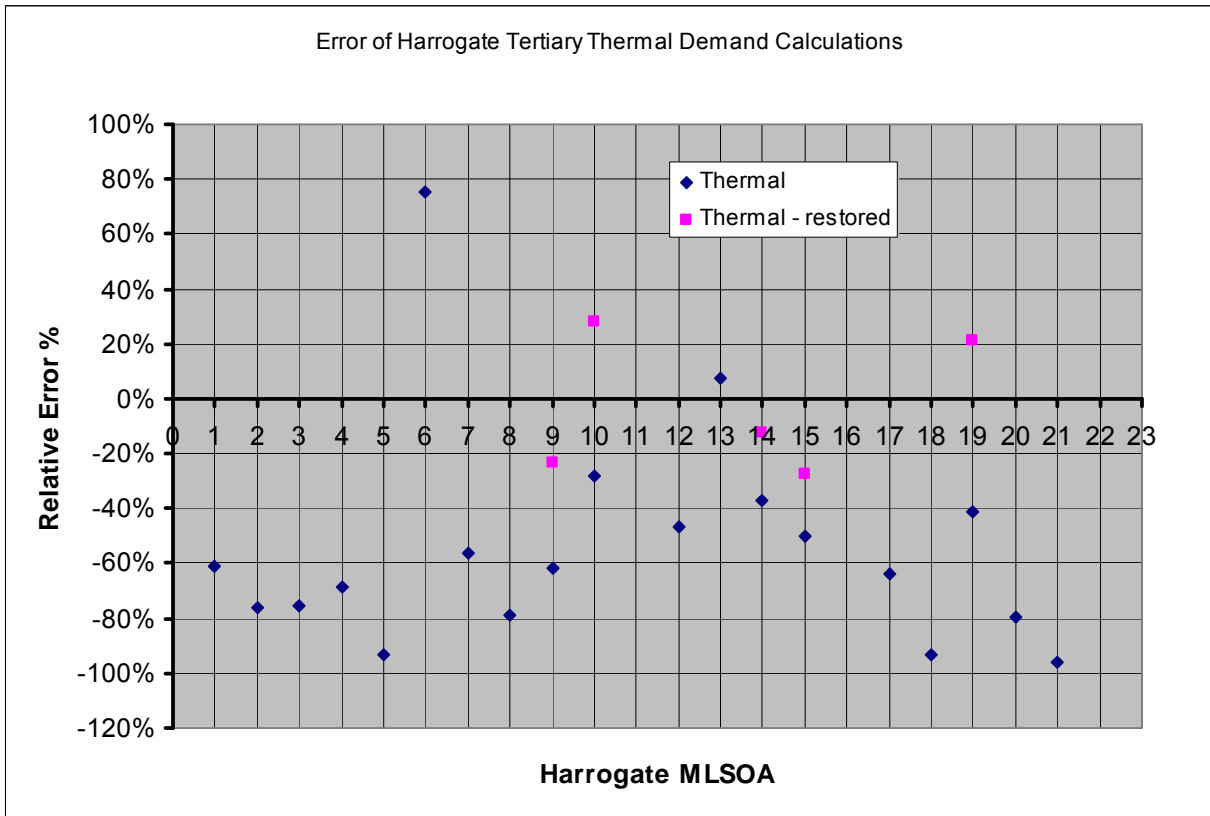


bias -9%
 Std. Dev. 13%

Tertiary scatter results



	bias	-52%	restored	12%
	std. dev.	33%		34%



		restored
bias	-54%	-3%
std. dev.	40%	26%

6.5. CHP Ops prediction errors

The purpose of the validation against the CHP Ops district heating site was to obtain an indication of the accuracy of the detailed thermal profile predictions. The prediction error in the annual demand is already described in Section 5.2. To isolate the *profile* related prediction errors the measured and predicted demand curves are normalised. The thermal demand model, described in Section 3.4, distributes the demand into daily amounts and then further into an hourly profile. To test the model, we look at the daily demand prediction error and then normalise the hourly profiles by the daily demand to isolate the hourly prediction error component.

The mean value of the profile error is zero because the profiles are normalised. The statistic used throughout to describe the error therefore was the sample standard deviation, given below in Equation 5.

$$S = \sqrt{\left[\frac{1}{(n-1)} \sum_n (x - \langle x \rangle)^2 \right]} \quad (5)$$

The standard deviation was normalised to the mean hourly or daily load to give an indication of the typical error at the hourly or daily level, respectively. The errors were calculated over a sample of 726 days. For the profiles, this provides at least 100 daily samples per 5 degrees temperature band. The results are summarised in Table 8 below.

CHP Ops Prediction Error		
Residential	Daily	13%
	Hourly	22 %
Tertiary	Daily	20 %
	Hourly	29-58 %

Table 8. Profile prediction errors

As described in Section 3.4, on the thermal demand modelling, the hourly thermal usage depends on a large number of factors many of which are vary randomly. The effect of these show up in the natural variation in profiles seen in Figure 24. The size of the measured residential profile variations are 11% - smaller than the prediction errors. For the tertiary, they are 26% - almost as large the typical prediction errors.

7. Discussion

7.1. Statistical Analysis

Tertiary

The tertiary sector data contains some large sources of potential error. Employee numbers are at the source of the demand calculation and 95% of the registered Limited companies have not reported this data. In Harrogate 015 MLSOA, 1249 out of 1994 companies are registered as Limited (62%). This suggests a significant underestimate of tertiary sector demand.

As described in the validation of tertiary demand calculations in Section 5.1, the restoration of this data can mitigate this underestimate to about 10%. The remaining sources of variations in the calculation, explained below, will dominate contributions to the resulting demand uncertainty.

For the remaining tertiary sector demand calculations based on provided employee numbers, there are potentially large systematic errors in the conversion of employee numbers to floor area - up to 75% at tertiary sub-sector level. This is because the conversion values are only available at large sector group levels. Fortunately, the conversion values should become more representative as the degree of aggregation across tertiary sub-sector increases.

Although the tertiary energy benchmarks come from a reliable source (CIBSE 2008), indications are that underlying demand variations in the tertiary sector are large – about 45% for thermal and 60% for electric. Once again, the accuracy of the benchmark as an estimate should improve with aggregation of sites.

Despite the large uncertainties in the input data described in Section 4.2, the error propagation results for Harrogate 015 estimate that random errors could be reduced to 8% for thermal and 9% for electrical demand. Whether this reduction is achieved in practice across the UK depends on having large numbers and good mixes of tertiary sites. The 30% uncertainty seen in the MLSOA scatter results suggest that the benefits of averaging are not fully realised. This is likely due to sources of extra variation and/or lack of statistical independence.

Residential

For thermal demand, the residential sector data starts with accurate data from EDF on the number of residential buildings per MLSOA. The greatest source of uncertainty lies in the demand of individual residences. We use benchmarks that are an average over different system behaviours and occupant numbers. The resulting thermal demand uncertainties of 15% to 40% are however reduced by aggregation to show up in the MLSOA statistics as 13% for thermal demand.

For electric demand, DECC consumption data is used directly and is expected to be accurate to within 5%.

The projection onto Zones and whole-UK method

The creation of Energy Zones in the continuation of work package 2 will involve a) further aggregation and b) geographic combination of regions designed to level temporal demand. Further aggregation will reduce the effects of random demand variation a little more and improve the repeatability of the results, although most of the aggregation has already taken place at the MLSOA level. Levelling of temporal demand will probably be achieved by having a good mix of industries and residential. With any one sector less dominant in the energy contributions, sector-average values will become more representative. At first sight then, Energy Zone demand calculations across the UK should have slightly reduced random errors but exhibit similar systematic errors.

7.2. Confidence in the Demand Prediction

A discussion of confidence levels in the various aspects of demand estimation is summarised in Table 9 below.

Confidence in energy indicators is derived from the completeness and accuracy of the indicator data. For example, the tertiary employee number indicators from Marketsafe provide a comprehensive coverage of UK company sectors but some of the records are missing and they must also be converted in to floor area using sector average conversion ratios.

Confidence in the benchmarks is derived from the institution that provides the benchmarks and their purpose. CIBSE is a respected institution and its TM46 benchmarks establish representative average energy consumption values to compare building performance against.

The confidence in the likely prediction error relies on the degree to which the project has tested the annual demand results against real demand data. Because this process can be time consuming and expensive, no testing was performed of residential electric annual demand because this came directly from measured values supplied to DECC.

We can have a high level of confidence in the models used for the distribution of annual demand (by profile) because these come from gas and electricity distributors who have a commercial stake in their reliability.

The confidence associated with the profiles themselves depends on the extent to which we are calculating the same demand. The confidence in the residential thermal profiles is good because it captures the main features and dependencies that characterise our zonal temporal thermal demand estimates.

Once again, the confidence in the likely profile prediction error relies on the degree to which the project has tested the temporal demand (or load curve) results against real load curve data. For example, our current confidence and level of knowledge in the likely profile prediction error for tertiary thermal demand is low because we have only been able to test predictions against a few buildings.

	Indicator Confidence	benchmark confidence	Annual Demand prediction error confidence	Profile model confidence	profile confidence	profile prediction error confidence
Residential Thermal	High - detailed Housing stock (2009) according to type and age purchased from market research company	High - detailed benchmarks validated on EDF Energy customers	Good - analysis of prediction over 20 Harrogate MLSOAs	High - a sound approach developed for gas grid load prediction	Good - captures the main features and driving factors	Medium - a limited validation from testing against 500 buildings on 1 site
Residential Electric	High - DECC data	High - DECC data	None - relying on accuracy of DECC data	High - a sound approach developed for electric grid load prediction	High - electricity seasonal hourly profiles developed by EDF Energy for the supply of its non-domestic customers. Curves reviewed on a regular basis.	none - relying on EDF Energy validation
Tertiary Thermal	Medium - employee indicator records sometimes missing though can be recovered	Good - benchmarks derived by CIBSE over a large number of buildings	Medium - indication of prediction validity from 5 MLSOA sample	High - a sound approach developed for gas grid load prediction	Good - developed for gas grid load prediction	Low - only tested against a few buildings
Tertiary Electric	Medium - employee indicator records sometimes missing though can be recovered	Good - benchmarks derived by CIBSE over a large number of buildings	Medium - indication of prediction validity from 5 MLSOA sample	High - a sound approach developed for electric grid load prediction	Good - developed for electric grid load prediction	none - relying on EDF Energy validation

Table 9. Description of confidence across the data and calculations performed in the demand estimation.

7.3. Further Validation Data Investigations

The validation approach can be further improved by applying it to some other CHP/district heating schemes across the UK. It would improve the confidence in the method and would add value to the project. For this purpose, an investigation on the CHP sites across the UK has been carried out (see Appendix 4).

Some of the CHP sites are identified as potentially significant considering the diversity of sectors being supplied by DH, location of the site, type of operator, etc. It is realised that none of the individual site would provide all the modelling inputs, therefore, several sites need to be investigated.

Demand Components	Modelled sector	Sector at Sites	DE Sites	Location	
Residential: Electric, Thermal	Detached house old, Detached house new, Flats old, Flats new	500 Flats: old (<1960) and new (2005)	EDFE CHP OPS	London	
		3212 Homes	Pimlico District Heating Undertaking (PDHU)	London	
		850 Residential flats	Aberdeen CHP	Aberdeen	
		160 Low energy homes	Milton Keynes Energy Park	London	
		18000 Houses	Energy Demand Research Project (EDRP)	Across UK	
		Flats (tower blocks)	Sheffield District Energy Network	Sheffield	
		620 contemporary residential units	Grosvenor Waterside Project	Central London	
		Residential properties	Southampton's district heating scheme	Southampton	
		166 flats	Sheffield Road	Barnsley	
		42 dwellings	Llanwddyn District Heating Scheme	Llanwddyn, Wales	
		4600 homes	Nottingham District Heating scheme	Nottingham	
		696 houses	Lerwick District Heating scheme	Lerwick	
		95 flats split between two blocks	St Pancras Housing Association (SPH)	London	
Tertiary: Electric, Thermal	School/University	Nursery school	EDFE CHP OPS	London	
		Primary school	EDFE CHP OPS	London	
			Lerwick District Heating scheme		
			Pimlico District Heating Undertaking	London	
			Citigen	London	
			Llanwddyn District Heating Scheme	Llanwddyn, Wales	
		University	Finning	Unknown	
			Nottingham District Heating scheme	Nottingham	
			Southampton's district heating scheme	Southampton	
			Imperial College	London	
		Hotel	Hotel	Finning	Unknown
				Lerwick District Heating scheme	Lerwick
				Southampton's district heating scheme	Southampton
		Pool	Swimming pool	EDFE CHP OPS	London
				Lerwick District Heating scheme	Lerwick
Nottingham District Heating scheme	Nottingham				
Hospital	Swimming and diving complex	Southampton's district heating scheme	Southampton		
		Hospital	Finning	Unknown	

		Lerwick District Heating scheme	Lerwick
	Health clinic, hospital	Southampton's district heating scheme	Southampton
Community centre	Community hall	EDFE CHP OPS	London
		Pimlico District Heating Undertaking	London
	Community centre	Llanwddyn District Heating Scheme	Llanwddyn, Wales
Commercial space		St Pancras Housing Association (SPH)	London
	Commercial premises	Pimlico District Heating Undertaking	London
		Citigen	London
Commercial space	10 commercial units, SPH head office	St Pancras Housing Association (SPH)	London
		Sheffield District Energy Network	Sheffield
Shopping centre	Large shopping centre, Supermarket	Southampton's district heating scheme	Southampton
		Nottingham District Heating scheme	Nottingham
	Market	Citigen	London
		Sheffield Heat and Power Ltd (SHP)	Sheffield
Local shops	Pimlico District Heating Undertaking	London	
Public building	Public buildings	Aberdeen CHP	Aberdeen
		Lerwick District Heating scheme	Lerwick
		Citigen	London
		Nottingham District Heating scheme	Nottingham
		Sheffield District Energy Network	Sheffield
Office	Office complex	Sheffield Heat and Power Ltd (SHP)	Sheffield
	Large office buildings	Southampton's district heating scheme	Southampton
	Offices and warehouses	Heathrow Airport	London
	Offices	Nottingham District Heating scheme	Nottingham
		Lerwick District Heating scheme	Lerwick
		Pimlico District Heating Undertaking	London
Others	Barclays Bank	Sheffield Heat and Power Ltd (SHP)	Sheffield
	BBC television studios	Southampton's district heating scheme	Southampton

Table 10. Overview of Demand Components by Validation Sites

The following schemes are identified as potentially interesting for further validation:

- Pimlico District Heating Undertaking (PDHU)
- Aberdeen CHP
- Nottingham District Heating Scheme
- Lerwick District Heating Scheme
- Southampton's District Heating Scheme

These sites cover all the sector energy model components. So, a data request has been send to the Pimlico and Aberdeen schemes. In the next step, the data will need to be further investigated and understood in order to apply the method.

8. Conclusions

The extended methodology described in this report has addressed the acceptance criteria outlined in Appendix 1. It provides a data-rich, bottom-up, calculation of energy demand on an MLSOA basis suitable for the UK. The calculation uses hourly models of aggregated electric and thermal demand derived from energy utility methods for predicting loads on gas and electric grids – the commercial stake of this approach ensures that it is fundamentally sound. Demand predictions have been compared with DECC annual energy consumption data for the Harrogate region and with the real measured thermal load on a UK district heating network.

The method is successful in calculating the annual residential energy demand. The combined EDF housing data provides an uncertainty of 13% on thermal demand calculations and DECC electric consumption is expected to be accurate to within 5%.

The results for the tertiary sector show larger uncertainties: approximately 30% for thermal and electric demand. The employee data restoration method developed seems to be effective in removing the energy underestimates seen in the initial calculation method. The company site dataset provides comprehensive data coverage of tertiary energy indicators but with low accuracy.

The (“bottom-up”) error propagation analysis indicates a low limit on random errors in the annual demand calculations. The figures are impressive: 1% on residential thermal demand, 8% on tertiary thermal and 9% on tertiary electric. However, the “top-down” MLSOA error scatter compared to the DECC figures suggest that the benefits of averaging are not fully realised. This is likely due to sources of extra variation and/or lack of statistical independence.

The temporal demand has been calculated with a large set of residential and tertiary profiles. The prediction of thermal load on a single district heating network (smaller than the target MLSOA scale) reproduced the main pattern and many of the features of the real measured thermal load. The total hourly prediction error seen on residential load was approx. 25%. The error on the tertiary load was higher because there were few of these buildings: over 40%. The hourly prediction errors would be expected to be lower on a larger aggregation of demand.

9. Recommendations

Recommendations for additions to task 2.0 “Demand Calculation Methodology”

The proposed work items P.1 to P.4 below complement the work performed in this task.

P.1 Extra Demand Validation Sites

2-3 extra sites with demand data sets will be compared with aggregate demand predictions. The comparison does not attempt to provide a rigorous validation but rather a comparison that exercises a sample of most demand components. The data sets will likely include sites such as the Aberdeen DH scheme, Nottingham DH scheme, EDRP data or the Pimlico DH scheme according to data availability and demand coverage.

Resource required: 24 – 36 FTE weeks (e.g. 6 weeks x 2 full time engineers per site + elapsed time contingency of about 25% in this example)

P.2 Sensitivity Analysis

A sensitivity analysis exercise has been proposed to explore the dependence of project outcomes on aspects of energy demand. WP2 will study different demand curve, clustering and classification parameters.

Resource required: approx 12 FTE weeks (e.g. 4 weeks x 3 full time engineers). N.B. this estimate will need revisiting when the sensitivity analysis activity is fully defined.

P.3 Map of UK Energy Demand

It is proposed to complement spreadsheet results of the UK energy demand calculation with multiple, detailed GIS energy demand maps.

Resource required: 4 FTE weeks (e.g. 4 weeks x 1 full time GIS engineer).

P.4 Map of UK Waste Heat

It is proposed to complement spreadsheet results of the UK waste heat calculation with multiple, detailed GIS waste heat maps.

Resource required: 4 FTE weeks (e.g. 4 weeks x 1 full time GIS engineer).

Recommendations for task 2.1 (Formation of Characteristic DE Zones)

For proceeding with task 2.1, it is recommended to provide an indicator of demand confidence, for example residential/tertiary ratio and proportion of Ltd companies (most subject to missing employee records). It would also be best to ensure a good mix of contributions within tertiary and residential sectors to benefit from averaging. Some annual demand values could also be re-calibrated with DECC data.

Recommendations for task 2.2 (Characterisation of industrial waste heat)

For proceeding with task 2.2, it is recommended to focus on the most likely and significant waste heat sources. It may also be necessary to create energy zones without the industrial waste heat estimate and then create an independent Energy Zone classification with waste heat potential that can be treated differently (e.g. within a sensitivity study) in the CHP modelling activity.

10. Future Work

Demand Zone Creation and Clustering

The hourly demand calculation method described in this report will be implemented in a robust database (mysql) in order to build the UK demand from each type of indicator, benchmark and profile in each of the UK's 8000 MLSOAs including approx. 4 million company records.

The resulting demand calculation by MLSOA then feeds a process of clustering adjacent MLSOAs into Demand Zones. The demand zones are created, *or designed*, from MLSOAs according to optimisation and constraint parameters. We anticipate several hundred to a over a thousand geographic Zones to result from this process.

Classification into "Characteristic" Zones

The classification of the geographic zones serves two main purposes. The first is to identify scales and patterns in the types of demand. The second is to reduce the energy plant design problem in order to facilitate an optimisation approach. The classification will reduce the geographic zone set into approx. 20 "Characteristic" Zones

Waste Heat Mapping

This task will assess, characterise and map the potential recoverable industrial waste heat across the UK. The waste heat created by the various high temperature processes of selected industries will be assessed and characterised. The quantity of thermal waste recoverable (in GWh/yr) per location will be mapped.

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⁶ Impact of heating, ventilation and behaviour on energy efficiency, building failure and comfort – oral presentation

⁷ Analysis and synthesis of load in order to optimise grid-bound energy systems (own translation)

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Appendix 1: WP2.0 Acceptance Criteria

Method for Demand estimation

- Describes 4 types of local energy demand: (residential, tertiary) x (thermal, electrical). Each type of demand will be composed of distinct contributions such that the demand estimation adapts to relevant local characteristics. The demand will be characterised by:
 - i) total annual demand level ;
 - ii) the distribution of this annual demand over daily and hourly periods using profiles.
- For the residential thermal type of demand, further research will be performed to identify the main influencing factors and related state of art demand modelling approaches.

Data availability & scalability.

- The sources of data for the demand estimation will be enumerated.
- The data required for the method should be available across the UK/GB.

Working assumptions

- A clear list of working assumptions in arriving at a demand estimate will be provided.

Validation

- Annual Demand calculations for each of the 4 demand types will be performed on at least 1 Harrogate MLSOA and validated against DECC consumption data.
- In addition, hourly thermal load curve predictions will be validated against the CHP Ops District Heating/CHP site. The validation will be performed on:
 - i) Aggregated thermal load
 - ii) Residential thermal model components

Statistical analysis

- A calculation of the confidence or likely error on the annual demand predictions based on Harrogate DECC energy consumption data will be given. In addition, a statistical comparison will be performed of hourly and daily demand predictions against measured data from the CHP Ops site.

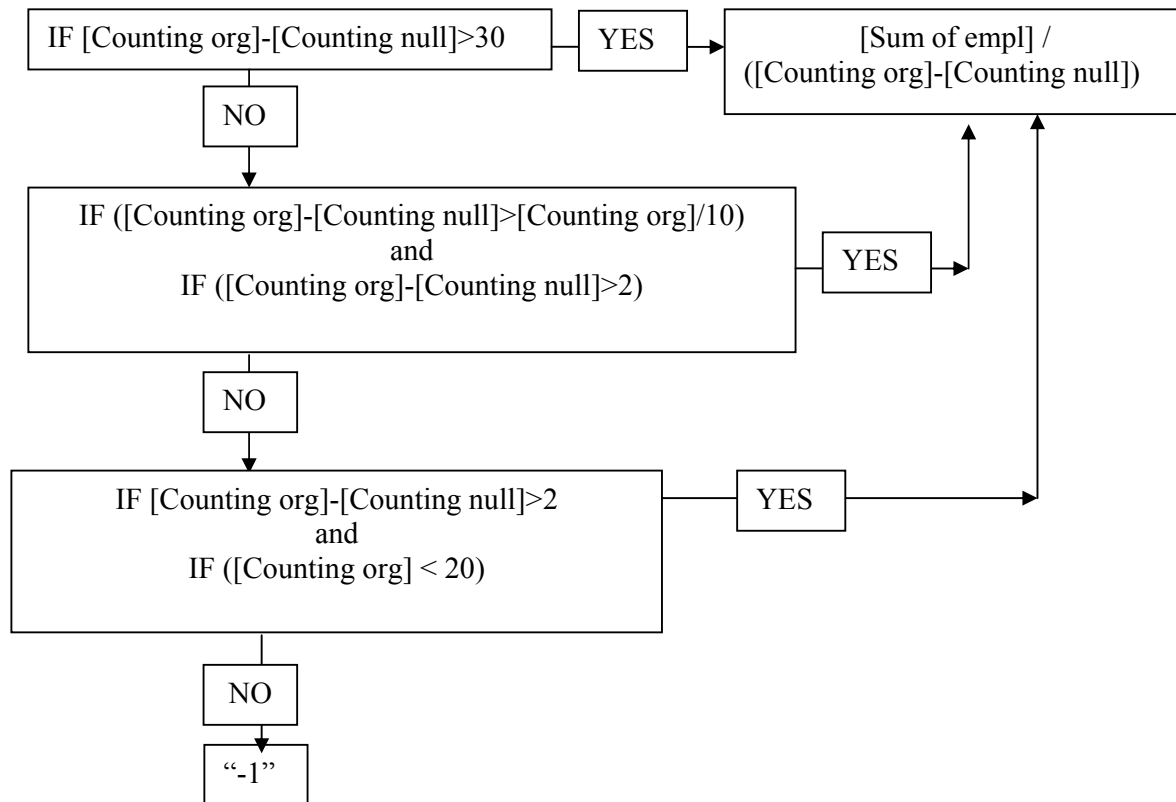
Scalability of validations against DE sites

- An analysis of potential sites for further validation of demand estimations will be produced. This will include a coverage table of demand estimation components by validation sites/data.

Appendix 2: Method To Restore Missing Employee Data

1. The First stage is a 2 way process on a DISTRICT LEVEL and also on a MLSOA LEVEL.

The process is similar at both levels, so it is only described once. The result is, as seen in the diagram below, gives an average number of employees. In the case that we do not have a sufficient number of companies with employee information the value of “-1”.



Avg_empl_number: Iif([Counting org]-[Counting null]>30,[Sum of empl]/([Counting org]-[Counting null]),Iif([Counting org]-[Counting null]>[Counting org]/10) And ([Counting org]-[Counting null]>2),[Sum of empl]/([Counting org]-[Counting null]),Iif([Counting org]-[Counting null]>2),[Sum of empl]/([Counting org]-[Counting null]),-1)))

Description:

Counting org - Counting number of companies

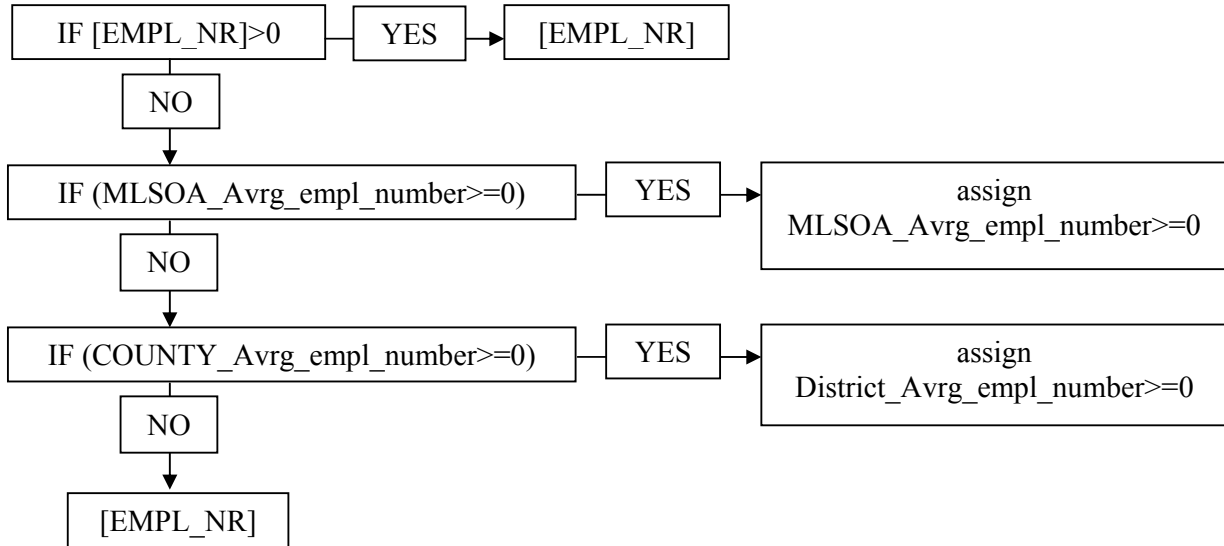
Counting null - Counting number of companies with no information on employee number

Sum of empl - Sum of all employees in the SIC of the company

2. The Second stage is assigning the average employee number to the companies which are missing this information.

This part of the procedure involves two steps. First step gives the companies with missing information on employees a new number calculated at the level of MLSOA. In the

second step, companies which are still missing information are given a new employee number calculated at the level of DISTRICT



Description:

EMPL_NR - Employee number
 MLSOA_Avrg_empl_number - Average number of employees for all the companies with that SIC in the MLSOA
 DISTRICTAvrg_empl_number - Average number of employees for all the companies with that SIC in the DISTRICT

EMPL_NR:

IIf([EMPL_NR]>0,[EMPL_NR],IIf(SIC_HG15_avrg_empl_number!Avrg_empl_number>=0,SIC_HG15_avrg_empl_number!Avrg_empl_number,[EMPL_NR]))

EMPL_NR:

IIf([EMPL_NR]>0,[EMPL_NR],IIf(SIC_avrg_empl_number!Avrg_empl_number>=0,SIC_avrg_empl_number!Avrg_empl_number,[EMPL_NR]))

Appendix 3: Profile Set Descriptions

Source	Bundesverband der Energie- und Wasserwirtschaft (BDEW) (formerly: Bundesverband der deutschen Gas- und Wasserwirtschaft (BGW))
Demand	Residential and Tertiary Gas
Profile Set	4 different residential profiles (detached house, apartments both old and new) 11 different tertiary profiles (e.g. offices, retail, pubs & restaurants, lodgings, banks and public buildings...) for unmetered customers
Data Sampling	Hourly values x 2-3 day types x 52 weeks
Access Rights	Published (in the document P2006/8). We have received written permission from the BDEW to use the method.
Usage Comments	The method has been developed for gas consumption prediction in Germany and depends on daily outside temperature values. The transferability to UK gas consumption seems possible using UK climate data.
Certification	<p>The method has been published by the Technical University of Munich (Prof. Wagner, Chair for Energy Economics and Applications Technology) on behalf of the BGW and regularly improved since. The standardised profile function was developed from 20 sets of 20 building samples across Germany - the justification for the statistical approach is described in (Hellwig, 2003).</p> <p>The method is mandatory by law and is used for balancing the gas usage of residential and tertiary customers. Today it is used by all known gas providers who are obliged to publish the parameters that apply to their gas grid.</p> <p>A published study (Kema, 2009) on the prediction of gas loads on a municipal energy utility gas grid, shows agreement to within a std dev of 10% in the winter.</p> <p>The error of the estimation method, when used for the UK, will increase to about 15% in the opinion of an expert user of the method from Thüga, the biggest association of city energy utilities in Germany. However, in the absence of a comparably detailed UK gas load prediction method, it is the best method currently available to us.</p>

Hellwig, M. (2003). Entwicklung und Anwendung parametrisierter Standard-Lastprofile. München, Technische Universität München.

Kema Consulting GmbH, 2009, "Analyse von Auswirkungen der Anwendung gängiger Standardlastprofile im Rahmen des Gas-Bilanzausgleichs", April 2009.

Source	EDF Energy Demand Forecasting
Demand	Residential Electric
Profile Set	Domestic Unrestricted (PC1) and Domestic Economy 7 (PC2) electric consumption profiles
Data Sampling	48 x ½ hourly estimates of electric load x 365 days for each of 14 demand regions (Grid Supply Points)
Access Rights	Data transmitted to EDF-EIFER. Permission has been granted to use within constraints identified in IP due diligence section of contract.
Usage Comments	This approach can be combined with DECC energy consumption data per MLSOA to compute a calibrated residential electric demand profile at MLSOA level.
Certification	<p>Under the deregulation of the electricity supply market in 1998, it was decided to balance the load from customers with below 100 kW peak demand using load profiles. Of the 8 profile classes specified by the <i>Profiling Taskforce</i>, two apply to residential demand: Profile Class 1 (PC1) profiles domestic Unrestricted consumption and PC2 profiles domestic Economy 7 consumption.</p> <p>The sampling fraction for domestic customers is approximately 1 in 2000. The validated samples across each Grid Supply Point (GSP) give a Group Average Demand (GAD). This forms the basis of the profile classes and is used for load prediction after applying regression analysis.</p> <p>The difference between profiled half-hourly consumptions and the actual metered readings is reviewed regularly and creates a GSP Group Correction Factor.</p>

Source	Bundesverband der Energie- und Wasserwirtschaft (BDEW)
Demand	Tertiary Electric (and Residential Electric)
Profile Set	One Residential profile 8 Tertiary profiles (distinguished by business and operational hours) and 3 Agricultural profiles Several sub-profiles for (domestic) hot water storage, night storage heating, and public lighting
Data Sampling	24 hourly estimates x 3 day types (working day, Saturday and Sunday) x 3 seasons (winter, summer, and transitional).
Access Rights	EDF-Eifer has received permission from the BDEW to use the profiles.
Usage Comments	
Certification	<p>The profiles have been established by the Technical University of Cottbus on behalf of the BDEW (VDEW at that time). They are based on measurements of 1200 sites from municipal utilities (e.g. Hamburg) and the large regional utilities during the 1980s. Geographical differences were not important</p> <p>The method predicts consumption of electricity of residential and tertiary customers. Today it is used as a basis for electricity transactions between energy companies for unmetered customers.</p>

Source	EDF Energy CHP Operations
Demand	Aggregated Thermal Demand
Profile Set	Thermal load of community heating project including several hundred housing units, a school, leisure centre.
Data Sampling	10 mins x 2 years
Access Rights	Cleared for use within EDF Group on the Macro-DE project. Not sufficiently aggregated to share raw data. Profile and demand predictions errors and analysis can be shared.
Comments	
Certification	<p>The aggregated demand contains over 500 flats dating from 1950 to 2005. Non-residential demand includes a Leisure centre with swimming pool, a school and a small nursery.</p> <p>The project should, therefore, show some aggregation effects.</p> <p>We have good access to the data and support from the operations manager.</p>

Source	EDF Energy Demand Forecasting
Demand	Residential Gas
Profile Set	End User Category (EUC) 1 profile (< 73.2 MWh p.a.; incorporates all residential)
Data Sampling	Daily demand estimates (out of an annual load profile) x 365 days for each of 13 demand zones
Access Rights	Data transmitted to EDF-EIFER. Permission has being granted to use within constraints identified in IP due diligence section of contract.
Usage Comments	The gas load profiles can be used to calibrate and cross-check the hourly prediction made for residential gas usage using the BDEW's method.
Certification	<p>Gas transporters are obliged, under the independent Gas Transporters' Uniform Network Code (http://www.igt-unc.co.uk/), to prepare non-daily metered demand estimations using profile services provided by xoserve (http://www.xoserve.com/).</p> <p>The EUC 1 profile is specifically modelled using a domestic subset of non-daily metered supply points - this approach was reviewed by the Demand Estimation Sub-Committee of the Uniform Network Code in June 2009 and confirmed.</p> <p>The number of samples for each of the 13 demand zones in the EUC 1 profile class ranged from 230 – 258 supply points (2956 across the UK) for the 1 year period ending March 2009.</p> <p>The performance of the profiling algorithms is compared with the actual measured consumptions at the supply points and published. For the EUC 1 profile class, the uncompensated percentage error across all zones for the 1 year period ending March 2009 was in the order of 5%.</p>

Source	EDF Energy Sustainable Solutions
Demand	Residential & Tertiary Thermal and Electric
Profile Set	Thermal (Residential, Office, Retail, Hotel, School) Electric (Residential, Office, Retail, School) Cooling (Office, Retail, Hotel)
Data Sampling	24 hours x 2 day types x 3 characteristic seasons.
Access Rights	Cleared for use within EDF Group on the Macro-DE project. Can also be shared at a sufficiently aggregated level.
Usage Comments	There is already experience of using these profile sets in the project. Can be used to cross-check other profile sets.
Certification	There is no readily available case history for these profiles. They have been developed by EDF Energy over a number of years and from different sources for use in bidding for and designing commercial CHP and DH projects.

Appendix 4: Further Validation Data Sets

Potential Validation Sites (CHP plants / District Heating System) in the UK

Green (data is collected) Orange (data is requested) Red (data is not going to be received in the time available)

No	Name of project	Location	Responsible authorities	Description of customers		Comments	Status update (09/2010)	Who	Sources
				Residential	Tertiary				
1	EDFE CHP OPS	London	EDFE	500 Residential units old (1960s) and new (2005)	1 Swimming pool 1 Primary school 1 Nursery school 1 Community hall	Daily data, 10 min data (on thermal load from 2003 to 2009) Outside temperature readings	Collected	Kevin McKoen/ Syed Monjur Murshed (EDF)	EDFE
2	Pimlico District Heating Undertaking (PDHU)	London	CityWest homes, City of Westminster	3,212 Homes	School 55 Commercial premises (Community Hall, Local shop, Offices)	2 CAT engines are in operation	Potentially interesting site Official request has been sent by ETI (on August)	Matthew Barton (ETI)	http://www.cwh.org.uk/main.asp?page=494
3	Imperial College	London	EDFE		University buildings	No residential block	Requested Energy Management of	Kevin McKoen/	EDFE

							Imperial college (on Sep)	Syed Monjur Murshed (EDF)	
4	Finning CHP site	Rotherham	Finning		hospital	It is a CHP site gas consumption, generator load, (electric power produced), available on hourly basis, no metered heat data (only plant consumption data, nothing on building)	Finning has the data, but needs customer approvals to use in the project	Stephen Neeson (Caterpillar)	http://www.finning.co.uk/default.aspx
5	CAT CHP sites	Various location	Caterpillar		Individual customer site: light industry	More information on aggregated CHP site would be helpful	Request sent to Stephen/Bryan	Bryan A Silletti (Caterpillar)	
6	Heathrow Airport	London	EDFE		Offices and warehouses	No residential block	Requested (on Sep). the plant has now ceased operations	Kevin McKoen/ Syed Monjur Murshed (EDF)	EDFE
7	Aberdeen CHP	Aberdeen	Aberdeen Heat and Power Ltd. (belongs to Aberdeen City Council)	850 Residential flats	8 public buildings	Separate CHP projects (Stockethill, Hazlehead, Seaton – flats, Seaton - public buildings)	Potentially interesting sites David Clarke, CEO of ETI has send the request to the Aberdeen City Council (on Aug)	Matthew Barton (ETI)	http://ieu-ltd.com/aberdeen-heat-power-ltd
8	Milton Keynes	Milton	UCL/National	160 Low		Hourly energy data	Contacted with	Kevin	http://eprints.ucl.ac.uk/

	Energy Park	Keynes	Energy Foundation	energy homes		in 1989, Hourly room temperature data in 29 dwellings	Tadj Oresczyn, Director of the UCL Energy Institute. It might consist of some tertiary sites need to check	McKoen/ Syed Monjur Murshed (EDF)	2305/1/Microsoft_Word_-_CP-UCL-04-NCEUB06-conf-MKEP-Revisited-Temperature-v1.9-04apr06-AJS.pdf
9	Sheffield District Energy Network	Sheffield	Veolia Environmental Services	Flats (tower blocks)	commercial and public sector buildings, such as theatre, court, university, galleries	140 Buildings currently connected to the District Energy Network	Potentially interesting sites Need to contact Request can be made for a particular site	Matthew Barton (ETI)	http://www.veoliaenvironmentalservices.co.uk/sheffield/pages/district_customers.asp
10	Energy Demand Research Project (EDRP)	Various location	EDF Energy, E.ON, Scottish Power and Scottish and Southern Energy. Managed by Ofgem (on behalf of the Govt.)		Smart meters in around 18,000 houses		Potentially interesting sites Out of scope of MacroDE project as the consortium needs significant time and resource to collect the trial data and to work with it	EDF/ETI	http://www.ofgem.gov.uk/sustainability/edrp/Pages/EDRP.aspx
11	Sheffield Heat and Power Ltd (SHP)	Sheffield	Sheffield Heat and Power Ltd (SHP)		Castle Market (33 permanent shops), Office complex, Barclays Bank	Individual sites are serviced	Need to contact	ETI	
12	Grosvenor Waterside Project	Central London	Vital Energi	620 contemporary residential units	A gym, spa, juice bar and business centre	Vital also operates DH schemes in other cities Edinburgh, Leicester, North London, Belfast, etc	Need to contact	ETI	http://www.vitalenergi.co.uk/CaseStudy_GrosvenorWaterside1.html

13	Southampton's District Heating Scheme	Southampton	Southampton Geothermal Heating Company Ltd (SGHC) (Southampton City Council and Utilicom)	Residential properties	Several large office buildings, a hospital, a health clinic, a university, a large shopping centre, a supermarket, several hotels, BBC television studios, one of Europe's largest shopping complexes, and a swimming and diving complex	Several DH schemes exist in different locations in Southampton, Request can be sent for a particular scheme	Potentially interesting sites Need to contact	ETI	http://www.southampton.gov.uk/s-environment/energy/Geothermal/
14	Sheffield Road	Barnsley	Berneslai Homes, Barnsley Metropolitan Borough Council (BMBC)	166 flats, arranged in three blocks		Wood fired Communal Biomass Heating, Social housing	Need to contact	ETI	http://www.barnsley.gov.uk/online
15	Llanwddyn District Heating Scheme	Llanwddyn, Wales	Powys County Council and Powys Energy Agency Dulas WoodEnergy Ltd	42 dwellings	A school, a community centre	Wood-chip boiler, Rural district heating	Need to contact	ETI	http://www.dulas.org.uk/project/detail.asp?project=24&id=25
16	Citigen	London	Citigen, owned by E.ON		Mainly commercial and public buildings: historic Guildhall, the Barbican Arts Centre, the Guildhall School of Music and Drama, the Museum of London and London Central Markets	Besides electricity and hot water, chilled water is supplied for air conditioning	Need to contact	ETI	http://www.eon-uk.com/generation/citigen.aspx

					(Smithfield) as well as other major commercial customers				
17	Nottingham District Heating Scheme	Nottingham	Enviroenergy Limited, owned by Nottingham City Council	4600 homes	National Ice Arena, the Broadmarsh and Victoria shopping centres, the Inland Revenue offices beside the canal, Victoria Baths, the Nottingham Town Hall, Capital One's UK headquarters and Nottingham Trent University	A coal-fired power station and a waste incinerator. Currently undergoing a £1.9m expansion	Potentially interesting site	ETI	http://www.enviroenergy.co.uk/index2.htm
18	Lerwick District Heating Scheme	Lerwick	Shetland Heat Energy and Power Ltd	301 Houses owned by council, Hjaltland and 395 Privately owned houses	Sports centre with swimming pool, 3 schools, the largest pelagic fish factory in Europe, a dairy (using heat for pasteurisation), residential care centres, a library, the main hospital, offices, retail premises, museum, hotels and guest houses, public buildings, council	Serving both domestic and non domestic properties in Lerwick since 1998	Potentially interesting site	ETI	http://www.sheap-ltd.co.uk/
19	St Pancras Housing Association (SPH)	London	SPH	95 flats split between two blocks	a community centre, 10 commercial units, SPH head office	Operated and maintained by housing associations		ETI	http://www.originhousing.org.uk/

References:

1. Combined Heat & Power Association: http://www.chpa.co.uk/case-studies_19.html
2. Xergi Ltd. & Xergi Services Ltd: <http://www.xergi.com/en/chp/references/chp-for-district-heating.html>
3. ETI MacroDE Deliverable 1.2: Design Practice Characterisation Report, Example Case Studies Appendix F.doc
4. DECC: Large scale CHP schemes in the United Kingdom, www.decc.gov.uk/assets/decc/statistics/source/electricity/dukes5_12.xls

Appendix 5: Gas Consumption and Thermal Demand

Specific Building Demand

- Gas boiler efficiency (typical) taken as 80% (deliverable 1.1 project framework document)

Aggregated Demand

- BRE domestic fact file: Energy Balance of the housing stock (2001)
1,365 PJ of delivered energy from gas for UK households
1,670 PJ of delivered energy for thermal uses
~1166 PJ of useful thermal demand (excluding useful gains)
→ national residential ratio of thermal demand : gas consumption = 0.85
This includes thermal system efficiency, proportion of gas thermal coverage, cooking ...
- A similar reasoning for the tertiary based on DECC Energy Consumption in the UK, service sector data tables (2009):
8,400 thousand tonnes of oil equiv. (ttoe) final energy natural gas consumption
10,100 ttoe final energy for thermal uses
~ 7100 ttoe of useful thermal demand
→ national tertiary ratio of thermal demand : gas consumption = 0.84

Appendix 6: Tertiary Profiles

Tertiary Gas profiles

Name	Description
Commerce/Trade/Retail	contains all retail sectors, e.g. food, clothes, ...; shops that are open only during daytime.
Local authority, bank and insurance, non profit organisation	Financial and public services, NGOs, NPOs
Pub and Restaurant	Pubs, Bars and Restaurants; Serving food and drinks
Accommodation	Lodging and Accommodation; offering a place to sleep, not necessarily food and drinks
Bakery	Bakeries open very early in the morning, esp. for making new bread
Paper and Print	Paper manufacturing and print houses
Metal and Car	Garages/repair shops
Laundry	have high hot water usage
Business in Household	Small private business that do not have offices in separated buildings, only a separated room in the house of the owner
Other Operational Service	Other services
Gardening	Plant breeders

Tertiary Elec profiles

Name	Description
Business with opening hours between 8:00 and 18:00	Business with demand hours during the day and much less during the night and at weekends, e.g. offices, doctors, lawyers, repair shops, print shops, schools, nurseries, administrations, banks
Business with high evening demand	“light-oriented” business, e.g. gas stations, pubs, leisure facilities, fitness centres, youth centres
Business 24/7	Businesses that have even demand all day long, e.g. waste water plants, communal facilities, cooling warehouses, stores with high demand of cooling devices, air conditioning or ventilation
Stores	Business with longer opening hours than 18:00 and partly working on Saturdays, e.g. barbers
Bakers’ shops and Bakeries	Bakers’ shops have a high demand during the night, usually starting at 3:00, while the demand during the day is comparatively low (only bread selling stores are classified above)
Weekend Business	Main activities of the business are at the weekend, e.g. clubs, carwashes, cinemas, sport facilities
Business in general	If no other profile fits
Small dairy farming and small animal husbandries	Small agricultural business with milking or feeding times in the morning and evening (larger business show demand during open hours as business between 8:00 and 18:00)
Other small agricultural business	Agricultural business and household in one profile
Agricultural business	General agricultural business, that is not represented in one of the other two agricultural profiles