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Statistical models to infer gas end-use efficiency in individual dwellings using smart metered data

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ABSTRACT

Residential buildings can significantly contribute to the European Union's 2020 efficiency energy targets. For this reason, energy distributors and suppliers are required to provide assistance to householders to reduce energy end-use. This paper develops statistical modelling methods that can be used by suppliers to infer the gas fuel efficiency of buildings in their residential portfolio, in order to deliver improved energy management services to consumers. The study begins by estimating individual statistical building energy models for a sample of consumers and presents the resulting distribution of independent parameters. These parameter distributions are then characterised by regression models using descriptive household data that is generally known by the consumer and can be easily gathered by the energy supply company. These models are then used to compare the inferred energy end-use efficiency of the household (cooking, hot-water and space heating) to similar dwellings. Buildings with higher-than-expected gas consumption can be targeted for energy efficiency programmes.

1. Introduction

In the European Union (EU), residential buildings are responsible for 26% of annual energy consumption and 37% of this energy is consumed as gas (European Commission, 2014). Domestic gas consumers can therefore make a significant contribution to the EU's 2020 targets of: (1) a 20% reduction in greenhouse gas emissions from 1990 levels; (2) a 20% increase in energy from renewable resources; and (3) a 20% improvement in energy efficiency (European Commission, 2009); and thus help to meet the objective of decarbonising energy end-use in Europe.

To help realise such improvements and a reduction in fossil fuel imports, the EU has mandated that smart meters are made available to residential gas consumers in each member state, except those states where an adverse cost benefit has been established (Official Journal of the European Union, 2009). This has resulted in the on-going installation of these meters in many countries across the EU. These include the United Kingdom (UK) where 22 million are planned for installation by 2019 and France, where 11 million could be in place before 2020 (Hierzinger et al., 2013). In such countries, consumers will have access to high resolution time-of-use consumption data. Sampling intervals for smart meters are typically hourly (or less) compared to monthly (or more) for traditional manually-read meters. Access to such high-frequency data will enable consumers to manage their gas consumption more effectively and identify readily achievable energy savings.

The EU has also recommended that energy distributors and/or suppliers provide assistance to consumers to help reduce their energy consumption. In this regard, each EU member state can implement an 'Energy Efficiency Obligation Scheme' to ensure that suppliers achieve energy savings each year from 2014 to 2020 that are at least equivalent to 1.5% of their consumers' average annual energy consumption between 2010 and 2012 (Official Journal of the European Union, 2012). However, because gas is used in the home for space heating, hot water production and cooking purposes, and since this consumption is dependent on factors such as dwelling size and occupancy, it is difficult for suppliers to identify appropriate energy efficiency measures for individual consumers based on their gas consumption data alone.

This study therefore develops and demonstrates a methodology that can be used to compare a household's gas consumption end-uses to those of other households with similar characteristics. Smart-metered gas consumption and household data (e.g. number of bedrooms and dwelling type) are used to develop statistical models which estimate energy end-use (e.g. space heating, cooking and hot water) for individual dwellings and compare these to a benchmark for dwellings with similar characteristics. This information allows energy suppliers to screen their customers and target

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Nomenclature

Abbreviations

A	area (m^2)
C	gas consumption (kW h)
F	fuel consumption (kW h)
HLC	overall heat loss coefficient (kW/°C)
HDD	heating degree day (°C·day)
MLS	multinomial logistic regression
N	number of air changes per hour (1/h)
NLS	non-linear least squares
Q	heat (kW)
T	temperature (°C)
U	U-value ($W/m^2 \cdot °C$)
V	volume of the heated space (m^3)

Subscripts

B	base
D	day
G	gain
IN	indoor
MP	metered period
O	outdoor
SP	set-point

Greek symbols

ε	model error
η	heating system efficiency (%)

appropriate energy efficiency measures at the most appropriate households. The methodology is demonstrated using daily gas consumption and household data collected for a sample of over 500 residential dwellings in Ireland.

The paper is organised as follows. It begins with a section on the current methods used to benchmark building energy efficiency using metered energy data. Because heating degree days (HDDs) are widely used in these methods and since they are used in the approach later described in this paper, a brief review of HDD theory is then given. The Methodology section describes data sources and two statistical inferential models. The first of these, based on non-linear least squares (NLS) estimates dwelling gas consumption based on parameters which we relate to gas end-uses. The second, based on multinomial logistic regression (MLR), estimates the relationships between these end uses and household characteristics. This latter model is then used to compare the relative energy end-use performances of households of similar characteristics. Following this Methodology section, a Results and Discussion section presents the statistical models, and by way of example, assesses the relative energy end-use efficiency of a sample of consumers with similar household characteristics. Conclusions and Recommendations are then presented.

2. Benchmarking

Benchmarking is the process of comparing an individual performance against a relevant standard, or benchmark. A wide variety of benchmarking methods have been developed for assessing household energy efficiencies using metered energy consumption data and, in almost all cases, these are based on HDDs. The HDD variable is a parameter based on outdoor temperature data that is traditionally used to estimate building heating system fuel consumption; the approach is described in detail in the next section.

Many building energy efficiency benchmarking tools have been developed that apply HDDs. For example, the US Environmental Protection Agency (US-EPA) has developed an Energy Star Score system for a range of commercial buildings that applies a regression based benchmarking tool (Energy Star, 2014a). The first step in this scoring system calculates an energy efficiency ratio for a building by dividing its annual energy use intensity (both electricity and gas) by that predicted by a regression model for the building type (Energy Star, 2014a). For example, the regression model applied for multifamily housing (or apartment) buildings has been fitted using a reference dataset of such buildings and is based on the number of dwellings per 1000 ft^2, the number of bedrooms per dwelling, the total HDDs and cooling degree days for the year, and the number of levels in each building (Energy Star, 2014b). The probability or percentile of the building's energy efficiency ratio is then found using a lookup table developed using energy efficiency ratios for the reference dataset (Energy Star, 2014a). The Energy Star Score for the building is simply 100 minus this percentile value. For example, a building with an Energy Star Score of 75 is bettered by only 25% of the reference dataset.

Home Energy Yardstick is an online tool that has been developed as part of the US-EPA's Energy Star program (Energy Star, 2015a). This tool benchmarks residential building energy efficiency using a 1 to 10 scoring system, where a score of 10 represents a home with the best energy efficiency level (Energy Star, 2015a, 2015b). This score is based on a statistical method and requires users to provide utility bill consumption data for electricity and gas, and their building's location, floor area and number of occupants (Energy Star, 2015a, 2015b). Energy suppliers in the US are encouraged to host this tool on their own web sites (Energy Star, 2015c).

In Europe, a Display Energy Certificate system is applied to large public buildings. These certificates are also based on metered energy consumption and building floor area and are used to present a building's annual energy use intensity (kW h/m^2/year) on an A1 to G scale, where an E1 rating corresponds to a typical building in the relevant building class (SEAI, 2015). These energy intensities are based on building floor area. Such normalised energy consumption parameters are a very common way of benchmarking building energy efficiency (Wang, Yan, & Xiao, 2012).

Each of the above benchmarking tools is based on energy intensity parameters normalised by building floor area, which presupposes that floor area data are readily available. However, it has been observed that many householders are unable to provide their building's floor area when surveyed—75% in the case of a previous Irish housing quality survey (Watson & Williams, 2003) and 59% in the case of the smart metering survey used here. Accurate area data would therefore be difficult to collect for an energy supply company. Moreover, many variables other than floor area contribute to household energy use; these include occupancy patterns, no. of occupants and dwelling type (detached, semi-detached, etc.). These, too, should be considered in a comprehensive gas consumption benchmarking method. Therefore, instead of using an area-related energy intensity parameter, this study develops an alternative regression-based benchmarking method based on multiple household variables which are known to householders and can be easily obtained through phone interview.

3. Heating degree days

Heating degree days form the basis of almost all energy efficiency benchmarking models. They are based on the concept that the instantaneous heat demand for a building may be estimated as the product of the building's overall heat loss coefficient (HLC) and the temperature differential between the heated space and the surrounding environment. HDDs estimate the integral of this temperature differential over time, so that the fuel consumption of