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Characterising domestic electricity consumption patterns by dwelling and occupant socio-economic variables: An Irish case study

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ABSTRACT

This paper examines the influence of dwelling and occupant characteristics on domestic electricity consumption patterns by analysing data obtained from a smart metering survey of a representative cross section of approximately 4200 domestic Irish dwellings. A multiple linear regression model was applied to four parameters: total electricity consumption, maximum demand, load factor and time of use (ToU) of maximum electricity demand for a number of different dwelling and occupant socio-economic variables. In particular, dwelling type, number of bedrooms, head of household (HoH) age, household composition, social class, water heating and cooking type all had a significant influence over total domestic electricity consumption. Maximum electricity demand was significantly influenced by household composition as well as water heating and cooking type. A strong relationship also existed between maximum demand and most household appliances but, in particular, tumble dryers, dishwashers and electric cookers had the greatest influence over this parameter. Time of use (ToU) for maximum electricity demand was found to be strongly influenced by occupant characteristics, HoH age and household composition. Younger head of households were more inclined to use electricity later in the evening than older occupants. The appliance that showed the greatest potential for shifting demand away from peak time use was the dishwasher.

1. Introduction

Throughout the EU, there has been a move towards smarter electricity networks, where increased control over electricity generation and consumption has been achieved with improvements in new technologies such as Advanced Metering Infrastructure (AMI). Residential smart metering is part of this and is seen as a necessary pre-requisite for the realisation of EU policy goals for increased renewable energy penetration, residential demand side management opportunities and improvements in energy efficiency, for achieving ambitious 20/20/20 targets.

EU-27 energy-related greenhouse gas emissions (GHG) targets for 2020 (based on a 2005 emissions baseline) include a reduction of 21% in greenhouse gas emissions for the emission trading sector across the EU-27 countries and a 10% reduction for the non-trading sector across the EU. The 10% reduction across the EU-27 countries for the non-trading sector is broken up collectively for the different member states. Ireland has been assigned a target of 20% reduction in greenhouse gas emissions by 2020 [1]. Domestic electricity consumption is covered under the emissions trading sector scheme whilst the non-trading sector largely consists of transport and agriculture along with heat use in buildings. The Irish Government has committed to achieving a 20% reduction (compared to average energy use over the period 2001–2005) in energy demand across the whole of the economy through energy efficiency measures by 2020 [2] and has also set a target of 40% electricity consumption from renewable sources by 2020 [3]. Other EU countries have committed to achieving similar targets to that outlined above.

Electricity consumption patterns for domestic dwellings are highly stochastic, often changing considerably between customers. Fig. 1 shows two individual customer electricity load profiles, over a 24 h period for a random day. The differences between the customers are apparent with Customer 1 having two distinct peaks, one in the late morning and another in the evening time. Customer 2's profile on the other hand has a double peak in the late morning and no significant peaks in the afternoon or evening periods.

Residential smart meters have been installed in a number of countries around the world such as: Italy, Sweden, Netherlands, Canada and Northern Ireland [4]. In July 2009, the largest electricity supplier in the Republic of Ireland – Electric Ireland (formally Electricity Supply Board) – commenced a smart metering trial for the domestic sector and small-to-medium enterprises. The trial consisted of metering approximately 4200 residential electricity customers at half hourly intervals as well as recording a detailed list of socio-economic, demographic and dwelling characteristics

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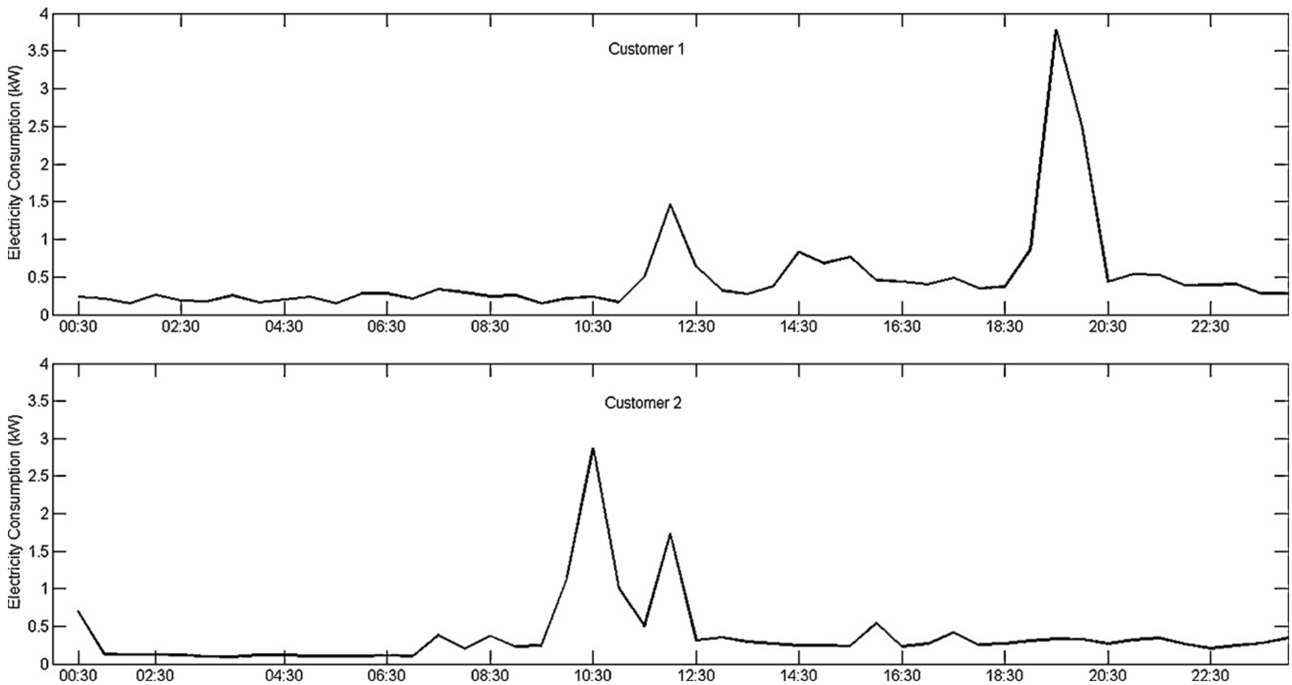

Fig. 1. Daily electricity load profile for an individual dwelling across a 24 h period.

for each household. The collection of such a detailed list of dwelling and occupant characteristics, combined with half hourly metering for 4200 individual customers offers a unique opportunity to investigate the drivers of electricity consumption patterns in the home. The dataset allows a detailed analysis of not only the affect of dwelling and occupant characteristics on total electricity demand but also on other load profile properties such as maximum demand, load factor and time of use (ToU) of maximum electricity demand.

The aim of this paper is to present results for dwelling and occupant characteristics that most significantly influence electricity consumption patterns in the home. As a result certain groups may be targeted where electricity savings and high renewable energy penetration can be achieved, thereby contributing towards meeting EU policy goals. Similarly, by determining electrical appliance characteristics that influence electricity consumption patterns at peak times will enable policy makers to identify measures to help reduce maximum demand.

2. Literature

There are various different approaches to modelling domestic electricity consumption, each with their individual strengths and weaknesses. The literature has been categorised below in terms of technique applied:

- Statistical/regression
- Engineering
- Neural network

Statistical/regression models can be considered to be both a "top-down" and a "bottom-up" method of modelling. Top-down approaches take data collected at an aggregate level such as national energy statistics, GDP and population figures to derive causal relationships between determinants and electricity consumption. Bottom-up models use data collected at an individual dwelling level to determine relationships between household characteristics and electricity use. Engineering and neural networks for the most part are considered to be a "bottom-up" modelling approach as they use data gathered at the dwelling level to infer relationships between electricity use and dwelling and occupant characteristics.

Statistical/regression models are particularly useful when a large dataset exists as they are based on real data and give a good understanding of electricity consumption patterns. However, they can be costly to implement and sometimes suffer from multi-collinearity between variables. O'Doherty et al. [5] used data from a National Survey of Housing Quality and applied a Papke-Wooldridge generalised linear model to infer a relationship between appliance ownership and electricity consumption. Their analysis showed explanatory variables that had a high significance for electricity consumption such as: dwelling characteristics; location, value and dwelling type as well as occupant characteristics; income, age, period of residency, social class and tenure type. Leahy and Lyons [6] applied an ordinary linear least squares regression using Irish Household Budget Survey data. Disposable income, household size, dwelling age and socio-economic group were amongst the variables that were shown to influence electricity consumption in the home. A variant of the statistical/regression approach is a Conditional Demand Model (CDA) first developed by Parti and Parti [7]. Monthly electricity bills over a yearly period were regressed against appliance ownership figures and demographic variables such as household income and number of occupants to disaggregate electricity demand into 16 different end-uses. This methodology showed the high significance of appliance ownership over electricity consumption patterns across a 24 h period.

Yohanis et al. [8] analysed patterns of electricity consumption in 27 representative dwellings in Northern Ireland. Electricity load profiles were characterised based on dwelling type, floor area, number of occupants, number of bedrooms, tenure, occupant age and household income. In particular, the authors found a significant relationship between domestic electricity consumption and floor area. Hart and de Dear [9] used regression to determine a relationship between external temperature and household electricity consumption in New South Wales, Australia. Their research concluded