Visualising Variations in Household Energy Consumption

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ABSTRACT

There is limited understanding of the relationship between neighbourhoods, demographic characteristics and domestic energy consumption habits. We report upon research that combines datasets relating to household energy use with geodemographics to enable better understanding of UK energy user types. A novel interactive interface is planned to evaluate the performance of specifically created energy-based data classifications. The research aims to help local governments and the energy industry in targeting households and populations for new energy saving schemes and in improving efforts to promote sustainable energy consumption. The new classifications may also stimulate consumption awareness amongst domestic users. This poster reports on initial visual findings and describes the research methodology, data sources and future visualisation requirements.

Index Terms: I.3.8 [Computing Methodologies]: Computer Graphics—Applications; H.5.2 [Information Systems]: Information Interfaces and Presentation—User Interfaces; H.2.8 [Information Systems]: Database Management—Database Applications;

1 INTRODUCTION

Energy consumption and carbon footprint reduction is of growing interest to individuals, organisations and government. Added pressure of EU carbon and emission targets set for 2020 and 2050 has meant that tackling energy consumption in the UK is of major concern. Reducing domestic energy consumption in particular is challenging due to large variations in household energy use. Patterns and trends in consumption levels in relation to housing, population, lifestyle and behaviours must be better understood in order to implement successful strategies in a movement to achieve efficient, sustainable and low carbon residential living environments.

Over recent years there has been a growing amount of academic and government-led research focused on energy consumption, carbon reduction and potential energy saving schemes; however, there is still limited knowledge of the relationship between consumption and measurable characteristics of the population. It is reported that UK domestic fuel consumption is strongly related to disposable income levels with other highly influential factors being dwelling type, household composition, property tenure and rural/urban location [4]. These findings, along with other research in the field, indicate that energy consumption patterns correlate to socio-economic and geographic characteristics and continued research in this area is needed in order to better understand the complex variations, allow for realistic comparisons amongst neighbours and facilitate better targeting of services and schemes. In this research we use data classification methods, analytical techniques and data visualisation to aid the interpretation and discovery of geographic and demographic variations in UK domestic energy consumption.

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2 GEODEMOGRAPHICS

Despite there being a body of relevant research correlating energy consumption with household or population variables, little research directly investigates the classification and evaluation of energy related variables with geodemographics. Geodemographic classification systems are used by geographers, policy makers and market analysts alike to segment the general population and identify trends and patterns based on typical user traits. Geodemographic data products such as Experian's Mosaic [6] or the free and open alternative Output Area Classification (OAC) [10], based entirely on the UK Census output, can greatly enrich consumer databases.

Large multi-variate dataset classification is ideal for residential energy consumption as previous research shows that human populations with similar characteristics and behaviours tend to cluster together. A research study [4] comparing consumption data with the 7 OAC Supergroups reveals variations between groups and clear correlations to household disposable income, property tenure and rural/urban location. We identify similar patterns when combining average electricity consumption data [3] with the 15 Mosaic Groups; Figure 1 reveals that the groups labelled 'Affluent' or 'Rural' display a higher average consumption (darker orange) than the others. The spatial variation of consumption within these groups is of particular interest as it highlights that energy use also varies geographically within these demographic clusters.

The selected datasets, weightings and methodology used for the classification process can all contribute to bias during data clustering. To reduce this bias it is necessary to use variables known to be relevant to the specific domain. As a correlation has been identified when combining geodemographics with energy consumption data, we propose that the geographical clustered of energy consumption data together with relevant variables of household and population characteristics could greatly improve the interpretation of both demographic and geographic variations in household energy usage. Such a energy-specific classification follows a recent call for geodemographics to be brought into the current data and technical era and follow more domain specific, problem centred approaches utilising the advances in visualisation and data exploration techniques [8].

3 SMARTER TECHNOLOGIES AND FEEDBACK

Within the energy industry there is already a substantial amount of household consumption data suitable for building an energy-based classification. The introduction of modern smart meters will; however, increase this data quantity exponentially. Smart meter technology allows for consumption to be recorded at frequent intervals and communicates this information to both consumer and energy supplier allowing for near real-time feedback of energy use. The introduction of smart meter technologies is expected to improve household consumption awareness as well as allow for better regulation of household energy demand. Smart meters form a major component of Smart Grids, which are estimated to reduce annual EU household consumption by 10% and carbon dioxide emissions by 9% [5]. Smart meter data could potentially improve our energy-based classifications for example introducing clusters related to high demand at certain times of the day or days of the week. In order to assess the potential for this granular dataset we are currently working in collaboration with the energy utility company E.ON on a project entitled 'Visualising the Smart Home'.

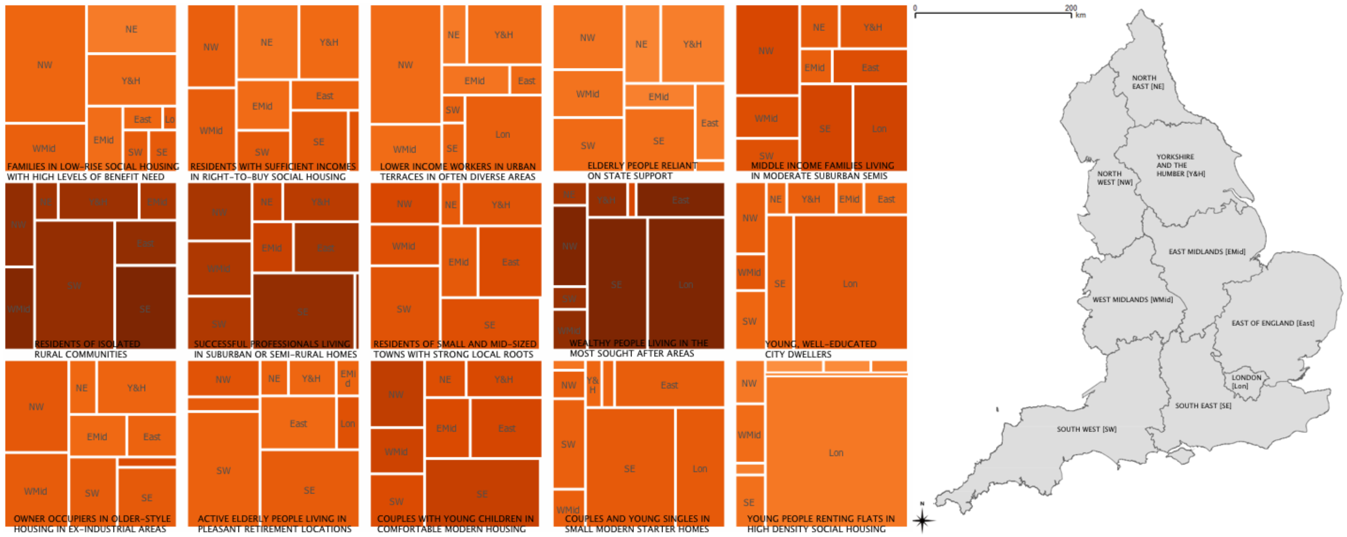

Figure 1: Mosaic Groups mapping English government regions sized by number of electricity meters, coloured by average electricity consumption

Increased pressure to reduce consumption combined with advances in meter technology has seen a growing need and demand for householders to be provided with more transparent and detailed understanding of energy use within their home. A significant amount of research is available evaluating alternative methods of consumer feedback. Relatively recent research identifies that social norms can be used effectively in the case of energy consumption reduction [1]. The research investigates the campaigns by *oPower* in the US, which compare households to a collection of neighbours with similar characteristics, and concludes that a small but continuous and sustained consumption reduction is achieved. These findings suggest that neighbourhood level comparisons based on geodemographic energy classifications could offer consumers a more reliable, understandable and concrete reasoning for saving energy.

4 Visualisation and Analytics

Energy management is one of the key domains where visual analytics can make an important contribution. With the introduction of smart meter technologies this statement applies as much to the high level energy demand and supply monitoring as to smarter controls and visual aids for householders. Technological advances in data visualisation offer real opportunities for research into energy consumption awareness with techniques that may provide personal views and interactive exploration of data. Rodgers and Bartram [7] encourage awareness and behavioural changes through tools and visualisations designed to make users aware of their energy use through non-intrusive and subtle visual stimuli.

Our research argues that the classification of energy-based variables could allow for variations in domestic energy consumption to be better understood. While data classification radically reduces data volumes and enables trends and clusters in large datasets to be identified with greater ease, they can also easily be misinterpreted. Some recent visual analytics research shows how exploratory data visualisation can be effective both during the clustering process and cluster decision stages (iVisCluster [2]) as well as for improving end-user understanding and overall comprehension (OAC Explorer [9]). This research highlights the benefits associated with classifying large datasets as well as taking steps to visualise the uncertainties that result from the clustering processes.

In our research we will use exploratory visualisation techniques to evaluate the use and benefits of our energy-based classifications. Requirements for the visualisations will be gathered at creativity workshops with E.ON staff during the 'Visualising the Smart Home' project.

5 Research Status

Having established a need for a geodemographic energy profile geovisualisation we are currently in the process of defining the classification system to be used, collecting datasets that may contribute and establishing visualisation requirements. Our poster will present some visual stimuli from the E.ON project as well as a description of our classifier and datasources to be used.

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