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Analysis and modeling of active occupancy of the residential sector in Spain: An indicator of residential electricity consumption

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HIGHLIGHTS

- Active occupancy profiles of Spanish dwellings has been obtained and modeled from Time Use Survey data.
- Occupancy profiles resulting from the model can be used to model domestic energy consumption.
- The presence of three peaks of active occupation was verified, which coincide with morning, noon and evening.
- Manual and incentive-based DSM programmes are considered the most suitable for Spanish dwellings.
- TV electricity consumption becomes important at aggregate level.

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ABSTRACT

The growing energy consumption in the residential sector represents about 30% of global demand. This calls for Demand Side Management solutions propelling change in behaviors of end consumers, with the aim to reduce overall consumption as well as shift it to periods in which demand is lower and where the cost of generating energy is lower. Demand Side Management solutions require detailed knowledge about the patterns of energy consumption. The profile of electricity demand in the residential sector is highly correlated with the time of active occupancy of the dwellings; therefore in this study the occupancy patterns in Spanish properties was determined using the 2009–2010 Time Use Survey (TUS), conducted by the National Statistical Institute of Spain. The survey identifies three peaks in active occupancy, which coincide with morning, noon and evening. This information has been used to input into a stochastic model which generates active occupancy profiles of dwellings, with the aim to simulate domestic electricity consumption. TUS data were also used to identify which appliance-related activities could be considered for Demand Side Management solutions during the three peaks of occupancy.

1. Introduction

In the context of a Smart Grid, the residential sector must be considered as a basic and integral component, due to the high percentage of energy consumption involved in this sector, as well as its high potential for Demand Side Management (DSM). A household can even be considered as a microgrid, taking into account that its energy portfolio can potentially consist of distributed generators, energy storage devices and electric loads, conventional grid supply and DSM (Kriett and Salani, 2012).

The average worldwide energy consumption in the residential sector is around 30% of total consumption (Swan and Ugursal, 2009; Kagvic et al., 2010). In Spain, households consume 17% of all total energy and 25% of electricity (Proyect SECH-SPAHOUSEC, 2011). These percentages are similar to those of neighboring countries. Moreover, electrical consumption in the residential sector has been increasing due to the growing number of residential housing units and the increasing number of their appliances (Gago et al., 2011; Yu et al., 2010). Owing to the large energy consumption within the residential sector, any energy saving action applied to this sector will have a significant impact in fulfilling the policy objectives of reducing energy consumption and CO_2 emissions (Kagvic et al., 2010; Directive 2009/28/EC, 2009; Kyoto Protocol, 1998).

The domestic sector has also significant impacts on peak electricity demand periods throughout the day, which may result in peak congestion of the grid, hence creating significant impacts on system costs because of the need for higher marginal cost generation and increasing grid reinforcement investment (Torriti, 2012).

The use of more efficient equipment would reduce consumption (Arghira et al., 2012). In addition, one of the proposed measures to

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reduce electricity demand in homes is to provide consumers with information regarding their consumption (De Almeida et al., 2011). This information allows the users to detect electricity misuse, and to restructure their consumption, by using energy in the hours of the day in which the electricity rates could be cheaper, or in periods that allow for self-sufficiency by employing installations based on renewable energy sources. Power consumption can be reduced if the energy use is known (McKerracher and Torriti, 2013; Gans et al., 2011; Ueno et al., 2006; Abrahamse et al., 2007).

In countries like Spain, measured data from electricity consumption of individual households via advanced metering technologies is likely to be unavailable for some time because their installation and use are still very limited (Torriti, 2012). Moreover, in order to determine a break-down of energy end-use, accurate measurement of energy use in households is required. For example each appliance would require a device that would make the measurements complex and costly (Widen et al., 2009). Obtaining this information through models might be a feasible option.

In the literature there are different types of models designed to determine the energy consumption habits in the home (Kagvic et al., 2010; Widen et al., 2009; Capasso et al., 1994; Yao and Steemers, 2005; Paatero and Lund, 2006; Richardson et al., 2010; Widén and Wäckelgård, 2010). Within the classification made by Swan and Ugursal (2009) accurate results are obtained with the so-called bottom-up models, which can reach good results with high time and spatial resolution (Widen et al., 2009). In addition, this type of models can potentially assess the impact of specific energy saving measures, like changes in habits or the use of more efficient domestic appliances (Kagvic et al., 2010; Widen et al., 2009). Applying bottom-up models does not imply a great complexity but, inconveniently, their implementation requires the use of an extensive database of empirical data (Kagvic et al., 2010).

Bottom-up models start from the smallest possible units of a system and successively aggregate these units to reach higher system levels (Widen et al., 2009). The consumption in dwellings is determined through an analysis of housing characteristics and types of appliances, as well as the behavior of their occupants. Among all this information, the data of active occupancy (i.e. when people are home and not sleeping) are of great importance because they are highly correlated with residential electricity demand profiles (Torriti, 2012; Capasso et al., 1994; Yao and Steemers, 2005; Paatero and Lund, 2006; Richardson et al., 2010). When people are in the household and not asleep, the household activities can be related to the use of different appliances (Widen et al., 2009; Widén and Wäckelgård, 2010; Richardson et al., 2008). As housing occupancy and activities of its inhabitants change throughout the day, the electricity consumption associated with a large number of appliances will also vary.

Large data sets describing the number of active occupants in houses are not readily available. Due to the limited information, the aim of this work is to analyze data from the Spanish Time Use Survey (TUS) and to extract information about active occupancy of the residential sector in this country. In recent years some researchers have begun to use national TUS data to establish a more reliable causal relationship between human behavior and residential energy use (Widen et al., 2009; Richardson et al., 2010, 2008; Widén and Wäckelgård, 2010; Chiou et al., 2011; López-Rodríguez et al., 2012), being considered as a complement, or even an alternative, to measurements of energy uses.

Once occupancy patterns of Spanish households were obtained, this information was used to implement a stochastic model that synthetically generates occupancy profiles of dwellings, with the same statistical features presented by the information gathered from the survey. Similar studies have been carried out in the UK by Richardson et al. (2008), and in Sweden by Widén and Wäckelgård (2010). The implemented model considers households with different numbers of occupants, an aspect that is very important to account for the sharing of appliances, lighting and heating or air conditioning. It also distinguishes between weekdays and weekends. Data generated by applying the model provide a larger data set for plotting the occupancy pattern of dwellings that could be used to model residential electricity use.

After obtaining active occupancy profiles another objective of this work is to identify residential active occupancy peaks, that is, the periods of the day where occupancy is higher. The activities of the occupants associated with the use of electric appliances were determined at these time slots. In addition, the variation of the occupancy is analyzed in order to identify strategies to follow in smart meters with the aim to diminish peaks and reduce consumption.

The structure of this paper is as follows. Section 2 introduces the methodology for extracting active occupancy patterns of Spanish household from TUS data; stochastically modeling active occupancy; and analyzing variations in active occupancy patterns. Section 3 presents the results from the implementation and validation of the occupancy model. Section 4 analyzes findings on active occupancy in relation to household activities and corresponding electricity demand loads. In Section 5 the changes in occupancy and their relation to DSM strategies are discussed. Finally, in Section 6 conclusions of the work are displayed.

2. Methodology

The main source of data for this work is the 2009–2010 Spanish TUS (Time Use Survey, 2009–2010), which was conducted using 19,295 people aged over 10, who at the time of the survey lived in a total of 9541 homes. The survey was carried out by the National Statistical Institute of Spain, following the EUROSTAT guidelines for harmonizing time use data. The survey refers to an annual period.

This survey includes information about the daily activities of the participants during the 24 h of one random day. In a diary, interviewees indicate, with a frequency of 10 min, personal information about the activities performed during the day, the place where they take place and whether they are accompanied by someone. As the diary data include the location of the participants, and also indicate which people live at the same address, this information can be used to identify the number of people that are at home and not asleep during the day. Therefore the number of active occupants in each household, for every ten minute interval, can be determined (Richardson et al., 2008; Widén and Wäckelgård, 2010).

Microdata corresponding to the TUS have been loaded into a database, in which, through a series of queries, information about the occupancy of each of the households included in the survey was obtained throughout a complete day. This provides the profile of active occupancy corresponding to each of the 9.541 households included in the survey. Moreover, thanks to diary information, it is also possible to know the activities that each of the residents is carrying out every 10 min, and consequently, to know the activities taking place in each household related to energy consumption.

As each person only completes the diary corresponding to one day results only become statistically significant at high levels of aggregation, in the same way as electricity demand profiles (Torriti, 2012).

2.1. Domestic building occupancy model

Using the information extracted from the TUS, a stochastic model based on Markov chain Monte Carlo techniques has been utilized. Each person in the household can be in either of two states: state 0, called inactive, which defines a person who is either outside the household or at home but sleeping; or state 1, called active, in which the person is at home and awake.