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A review of time use models of residential electricity demand



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ABSTRACT

Residential electricity demand in most European countries accounts for a major proportion of overall electricity consumption. The timing of residential electricity demand has significant impacts on carbon emissions and system costs. This paper reviews the data and methods used in time use studies in the context of residential electricity demand modelling. It highlights key issues which are likely to become more topical for research on the timing of electricity demand following the roll-out of smart metres.

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1. Introduction

Residential electricity demand in most European countries accounts for a major proportion of overall electricity consumption. Traditionally, electricity metering at a residential level has been conducted at a low time resolution, either on a monthly or bi-monthly basis. Most policy-makers, energy suppliers and energy

service companies base their policies, tariffs and projects based on average load profiles on daily or monthly basis. The recent and forthcoming high penetration of smart metering technologies in developed countries has increased the significance of time use data [1,2]. Time use data report activities carried out by people throughout the day [3]. They are becoming increasingly relevant for peak electricity demand issues. At what time residential end-users switch lights, heating and appliances on, for how long, and at what time they switch them off determines the individual electricity consumption profile in the household [4]. The sum of individual profiles in a neighbourhood or district determines the

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time-related electricity consumption of a specific section of the distribution network [5]. Peak loads in the transmission grid occur when on aggregate a vast amount of residential end-users is using electricity at the same time [6]. When this happens, typically in the late afternoon of a winter day, the costs and negative environmental impacts of meeting this extraordinarily high demand are higher than normal. This is because energy suppliers have to activate carbon intensive power plants to compensate for such increase in demand [7,8].

One question that scholars have been seeking to address for some time relates to how to measure the timing of residential electricity demand [9]. Various models have been deployed, from stochastic predictions of appliance use to weather-related deterministic models. One emerging approach consists of tracking people's practices in and out of the household, following the assumption that residential electricity demand is determined predominantly by the timing of human activities (e.g. travelling to work and taking children to school) [10]. This approach tends to rely on either measured time use survey data or synthetic stochastic models.

This paper reviews the data and methods used in time use studies in the context of residential electricity demand modelling. It reviews the literature on existing models for residential electricity demand in relation to the types of data they use (Section 2); describes modelling approaches used in time use studies (Section 3); reviews time use studies (Section 4); discusses some of the limits of time use approaches; and concludes by exploring how the research area of time use might evolve in the future (Section 5).

2. Data for modelling residential electricity consumption: a review of the literature

The literature on electricity demand makes use of different approaches to model the timing of residential electricity consumption. The approaches originate from different disciplines, including energy econometrics, electrical engineering, sociology of practice, environmental psychology and household economics. Traditionally, reviews of models of electricity consumption tend to focus either on the modelling method [11–13] or the discipline [14]. This review focuses on data with a view to critically examine existing datasets informing residential electricity demand and exploring the advantages and disadvantages of each approach in relation to the timing of residential electricity demand.

2.1. Models using actual or simulated end-use data

Electrical engineers use either actual or simulated end-use data to construct electricity consumption profiles. Average energy efficiency, average appliance power ratings and end-use features are typical examples of the type of input data required in electrical engineering models. The simulation component of this kind of modelling implies that residential electricity loads are forecasted even in the absence of historical data information on electricity use. Yao and Steemers [15] make use of a dynamic software model to generate load profiles of domestic space heating load for different types of dwellings based on occupancy patterns, appliance ratings and appliance ownership. Their study distinguishes between behavioural determinants of residential electricity consumption (which are associated with the weekly, daily or hourly basis when specific appliances are used) and physical determinants (which are associated with unchangeable variables like the size of the dwelling).

Shimoda et al. [16] construct residential electricity load profiles for different dwelling types and household features with a granularity of one-hour period. Their study, which is based in a urban

setting in Japan, shows that occupants' time use, appliance efficiencies, external temperature and dwelling thermal characteristics affect residential electricity consumption profiles. Papadopoulos et al. [17] apply a simulation software to model residential energy use in Greek households and compare the economic and environmental performance of different typologies of space heating. Oil fired boilers underperform in comparison with heat pumps, electric radiators and gas fired boilers.

Higher granularity models for residential electricity profiles need to rely on both behavioural factors, including psychological and sociological consumption motives, but also demographic and socio-economic factors. For instance, McLoughlin et al. [18] analyse how total electricity consumption, maximum demand, load factor and time of use of maximum electricity demand relate to different dwelling and occupancy socio-economic variables. Time of use tariffs consist of differentiated electricity prices for distinct times of the day (i.e. peak and off-peak tariffs). They find that dwelling type, number of bedrooms, head of household age, household composition, social class, water heating and cooking type play a significant role over total residential electricity consumption. A strong relationship is in place between maximum demand and household appliances (i.e. tumble dryers, dish-washers and electric cookers).

The employment of end-use data has the merit of providing close to reality proxies to residential electricity demand without having to rely on historical consumption data. This means that in some cases the physical and behavioural data used as input in the model can be integrated with time use data, hence offering a break-down of residential electricity loads which can be useful to Transmission System Operators (to balance demand and supply near real time), Distribution Network Operators (to differentiate tariffs) and demand side participation aggregators (to offer demand side response services to residential customers). However, most of the models reviewed above can hardly be extended or generalised to wider population samples. As a result, models relying on either simulated or actual end-use data can be complex to validate and implement.

2.2. Models using macroeconomic data

Energy econometricians use aggregate macroeconomic data (e.g. GDP, average income levels, population size, national energy prices) in order to correlate electricity demand profiles with socio-economics variables.

O'Doherty et al. [19] apply the Papke–Wooldridge generalised linear model from the Irish National Survey of Housing Quality. By exploring the relationship between electricity consumption and appliance ownership, they find out that dwelling characteristics, location, value, dwelling type, occupant characteristics, income, age, period of residency, social class and tenure type play an important role in explaining residential electricity consumption. Filippini and Hunt [20] rely on the framework of household production theory to model residential electricity demand as an input to the demand function. Their model controls for income, price, population, average household size, heating degree days, cooling degree days and the share of detached housing to assess residential “underlying energy efficiency”. Other studies use time series to assess the degree of correlation between residential electricity demand, on the one hand, and, on the other hand, household total final consumption expenditure, real energy prices and underlying energy demand [21–23].

Parti and Parti [24] make use of survey data on appliances and electrical billing data when developing their conditional demand analysis model. Because of their attempt to determine the use level of individual appliances based on regression methods, the behavioural data inputting into their model are highly theoretical

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