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Synthesising electrical demand profiles for UK dwellings

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A R T I C L E I N F O

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Empirical domestic energy demand data can be difficult to obtain, due to a combination of monitoring, data access/ownership and cost issues. As a result, it is quite common to see domestic energy assessments based on modelled energy consumption. When looking at quite specific metrics of energy consumption, such as minutely domestic electrical demands, the data that does exist tends to be for a relatively small number of homes. The methods presented here provide a starting point for extrapolating this information so that such data can be used to represent a much larger group of homes, and therefore have wider applications. While limitations still exist for the extent of this extrapolation, issues such as diversity of demand and occupancy variations can be accommodated within an appropriate statistical analysis. The method also demonstrates that, by using the synthesis method to characterise the patterns within a daily domestic demand pattern, informed estimations can be with regards to the type of activity being carried out within the dwelling. Synthesised aggregated datasets (representing a larger group of dwellings) are also compared to real demand profiles from substations, to investigate whether similar patterns are being observed. This is part of the Adaptation and Resilience in Energy Systems (ARIES) project, looking at energy demand and supply in a future climate.

1. Introduction

Projections, and baseline estimations, for domestic energy demand data is often provided in the form of annual energy consumption. It is quite commonly in the form of modelled data, or information that has been extrapolated from proxy data (such as energy trading figures [1]). When assessing the energy consumption of large sections of the building stock (e.g. substation areas and larger) several difficulties become evident, and this can be summarised as the difference between "bottom-up" data and "top-down" information. The former might involve taking data from individual dwellings and trying to scale-up (through a statistically appropriate sample) to something larger. The latter involves taking information describing a broader picture (such as nationwide energy consumption figures across the entire building stock), and interpolating down into something that describes a smaller number of buildings. It could be argued that there is a gap between these two forms of data; namely, there is a limit to both the upscaling of bottom-up modelling and downscaling of top-down modelling. Some stock models attempt to address this gap [2], but there is a high reliance on non-empirical assumptions.

If relying on empirical demand data, the task becomes even more difficult if a high temporal resolution is required. Minutely electrical demand profiles, as will be discussed, demonstrate quite diverse energy use patterns that change from day to day and for different dwellings. These profiles are, however, useful for understanding energy use in the home and making estimates for the effect of energy-saving measures. In non-domestic buildings, features within a daily electrical demand profile tend to be a composite of several activities (and are therefore smoother in shape), for dwellings even very short activities (like the boiling of a kettle) are evident within the profile. As a result, a domestic electrical demand profile (when shown at suitable temporal resolution) can appear as a series of power demand spikes stochastically superimposed onto longer periods of lower energy consumption that vary throughout the day. When modelling such profiles, and attempting to synthesise new, virtual profiles, this must be borne in mind.

Utility companies have long recognised the benefits of forecasting energy requirements, using this information to better manage energy generation and distribution systems. Advances in computing technology, and an increased awareness of energy efficiency, saw initial efforts to develop forecasting models in the 1970s and 1980s [3]. Many early models adopted a different approach [4], whereby a total hourly load profile was derived from the individual contributions of major household appliances. Such projections demonstrated a good correlation with historic power plant data,

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and could effectively replicate distinct profiles for different days (weekdays and weekends) and seasons.

Later work attempted to incorporate psychological factors within the models to account for the effect of occupant behaviour on energy consumption. Walker and Pokoski [5] introduced the concept of 'activity' and 'proclivity' functions, indicating whether the occupant was at home and awake, and the likelihood they would use a particular appliance at a given time, respectively. Capasso [6] used socioeconomic and demographic data to inform the load shape, and developed a methodology linking appliance use to human resources (e.g. eyes, ears, hands, etc.). This limited the simultaneous activation of certain appliances, e.g. a radio and television could not both be activated where the occupant only had resources to listen to one at a time.

Both these models have been highly influential [7], however subsequent work has needed to introduce additional functionality as renewable technologies become more integrated within the energy supply network. Renewables are a highly variable energy source and this has necessitated the analysis of demand profiles at a much finer temporal resolution [8–10]. Stokes' domestic lighting model [10] can generate minutely demand profiles for single dwellings; however, this high-resolution data demonstrates much greater variability between measured and generated profiles compared to data averaged over a number of dwellings or extended periods of time. This is a trait recognised by numerous model developers [10,11]. The Stokes model highlights that the purpose of the high-resolution data was not to replicate lighting demand, but to reproduce typical characteristics of use, such as duration of long term demand, or frequency and magnitude of irregular spikes. An opportunity for a more direct comparison between generated and measured electrical data is presented by Widen's model, where the profiles were derived from time of use (TOU) survey data [11]. A good correlation was demonstrated, but the comparison highlighted a number of notable differences: the model excluded the effect of standby power; average performance and operation characteristics were assumed for modelled appliances; and appliance use was difficult to model where there was no obvious link to specific activities.

The above models demonstrate an increasing reliance on extensive and varied ranges of data sources. This can present additional challenges for processing and applying the information effectively: Widen's interpretation of the TOU data contributed to inconsistencies between generated and measured data; Sanchez et al. were reliant on large databases which featured missing or incomplete datasets [12]; Paatero and Lund [13] noted differences in the methodology used to report data (e.g. some sources recorded weekly averages whereas others differentiated between weekday and weekend). The authors of this latter example adopt a statistical approach, using publicly available appliance data and consumer statistics to determine load profiles. Paatero and Lund argue that any reduction in accuracy arising from inconsistent data sources is compensated for by a considerable decrease in data requirements needed to inform the model.

Advances in computing have contributed to significant developments in load forecasting techniques, with a review by Alfares and Nezeeruddin [14] identifying up to nine categories to describe the range of methodologies applied. Unlike the previous models considered, the load forecasting techniques typically operate at an aggregate level; they report data for a substation or utility company on an hourly basis, and this can span short, medium or long term load forecasting periods, representing anything from a day (STLF), a year (MTLF) or even 10 years (LTLF).

While operating at a less detailed level, a high value is placed on the accuracy of load forecasting models, where Alfares and Nazeeruddin point out that a 1% reduction in the average forecast error can save hundreds of thousands of dollars. These models therefore need to be capable of considering a range of scenarios and environmental conditions, as well as the 'holiday' effect and seasonal wind-chill. Chow and Tram [15] adopted a hybrid approach to include a spatial load model, considering the effect of details such as distance to electric poles. Djukanovic et al. [16] included algorithms to calculate the impact of holidays, but also extreme weather events such as heat waves and cold snaps.

As we progress towards the UK's 2050 deadline for an 80% reduction in green house gas emissions, and renewables become more prevalent within the energy supply network, there is less emphasis on a need for highly accurate future projections, and more on identifying strategies to better match demand to a more variable energy supply. These tools can be used to inform or investigate future policy, but they must have the functionality to interrogate changes in a number of key areas, such as the application of new technologies, the influence of occupant behaviour, and the impact of a changing climate.

2. Domestic electrical demand data

The demand data discussed here will be at minutely resolution for individual dwellings, though the available substation data is at 10-minutely resolution (discussed later). This aids both an understanding of what might be going on inside a dwelling, but also the synthesis process itself (which requires this level of detail). The distinction, and different characteristics, of individual dwelling profiles and aggregated (i.e. several dwelling) profiles is particularly important and demonstrated below.

2.1. Individual dwelling data

Previous studies have discussed the basic characteristics that might be seen in an electrical demand profile [17]. Even with little prior knowledge of that particular dwelling, reasonable assumptions can be made about, for example, the existence of electrical showers, electric heating, and times of high and low occupancy [18]. The minutely resolution of these profiles allows such characteristics to be seen, and also enables times of peak demand to be discerned. Research elsewhere has shown the effect of averaging demand profiles over longer time periods [19].

The data used for this article is not intended to represent typical or average dwellings of the UK building stock – and such an approach (of representing millions of homes through a small number of profiles) would be statistically dubious in any case. Rather, this data will be used to demonstrate a novel methodology that could be carried out on any similar dataset.

The dataset has been introduced elsewhere [20], and consists of full-year, minutely electrical demand datasets for nine dwellings (used for this project) and partial datasets for other homes. The data is not accompanied by contextual information (e.g. technology inventory list, occupancy), but the described approach is only for upscaling to a larger number of similar homes in any case so this information gap is not seen as detrimental to the fundamental statistical approach. Due to both resolution and duration of monitoring, this data is relatively rare; as a result the dataset is not as recent as would be ideal. The implications of this are discussed later.

Two examples of the demand profiles used are shown in Figs. 1 and 2, representing winter and summer profiles. While an individual day will have specific features that might occur, essentially, at random, common features can still be discerned and, in the cases of Figs. 1 and 2, attributed to the fact that this is a domestic demand profile in winter and summer, respectively. Both profiles show features previously discussed, such as kettle/shower/cooking spikes (or other appliances with some form of electrical heating element), superimposed on top of a more predictable energy profile