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Synthesising electrical demand profiles for UK dwellings

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ABSTRACT

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

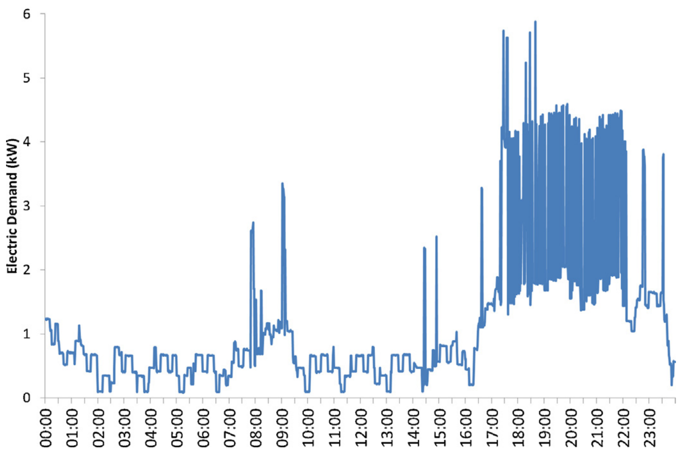

Fig. 1. Minutely electrical demand profile for one sample dwelling on December 21st.

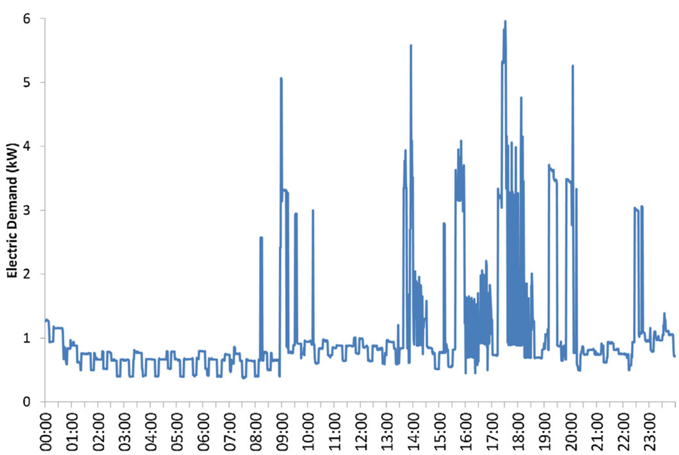

Fig. 2. Minutely electrical demand profile for one sample dwelling on June 18th.

that is dependent on occupancy. An underlying refrigeration cycle can also be seen in both figures but this varies slightly between the two profiles, with the higher external temperature in summer being a possible cause of higher refrigeration energy consumption in Fig. 2. Without information of the specific dwelling, and occupants, such analysis cannot be completely definitive, but the existence of such features (and their possible causes) will be important in building the methodologies described in this article.

2.2. Aggregated profiles

As discussed above, while an underlying trend can be seen within an electrical demand profile (relating to typical occupancy patterns for a working home), the partly stochastic power spikes have a low probability of occurring at exactly the same time every day and, likewise, at the same time for a neighbouring house. The result of this is that, when aggregating the profiles of many homes, these features do not superimpose directly. Therefore, for example, while 10 homes may have peak demands of 5 kW each, it is highly unlikely that the combined demand will be as much as 50 kW. This diversity effect is commonly referred to as After Diversity Maximum Demand (ADMD) [21].

ADMD is the peak demand per house (for a number of homes combined) and is useful for estimating the design requirements for grid connection and low voltage networks. For example, taking the nine dwellings of this study on December 21st, Fig. 3 shows how this average peak demand per house reduces as more dwellings are added. Even after just nine dwellings, the curve begins to plateau – though for a more accurate estimation of the ADMD value more dwellings should be added to this.

This diversity effect is further demonstrated in Fig. 4, where all nine dwellings have been aggregated together for the same day. The profile is clearly quite different to that of the individual dwelling, and the peak demand per house much less than that of Figs. 1 and 2. Similarly, the load factor (numerically the average demand divided by the peak demand, which quantifies the variability of the profile) is significantly different at 40% for Fig. 4, compared with 19% for Fig. 1. However, while this profile is relatively smooth for just the nine available dwellings, it is clear that there is still stochastic "noise"-like elements to the profile.

Therefore, both Figs. 3 and 4 suggest that more dwellings would be necessary to account for typical diversity across a group of dwellings. However, in the case of this dataset, there are only nine dwellings – hence the requirement for more synthetic profiles to

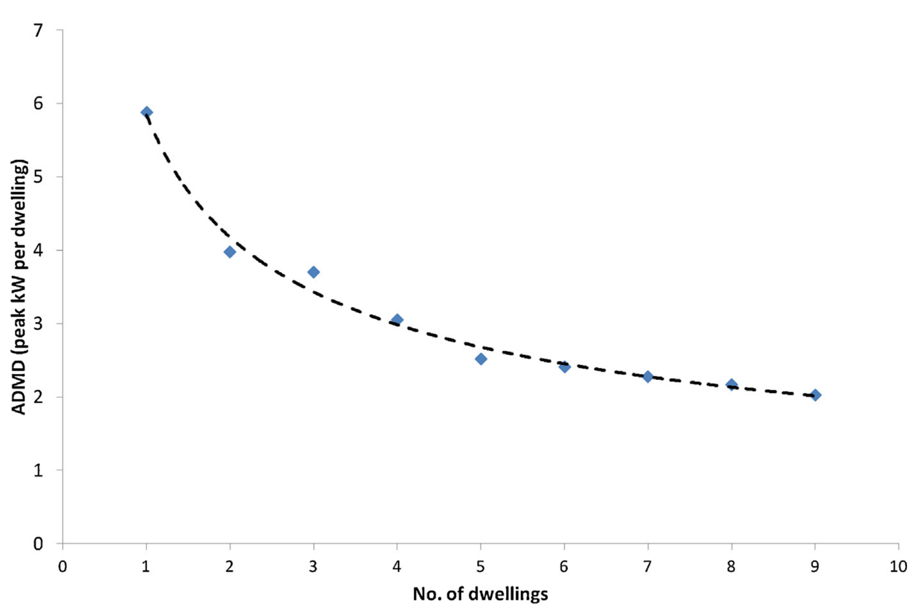

Fig. 3. The ADMD curve for nine dwellings on December 21st.

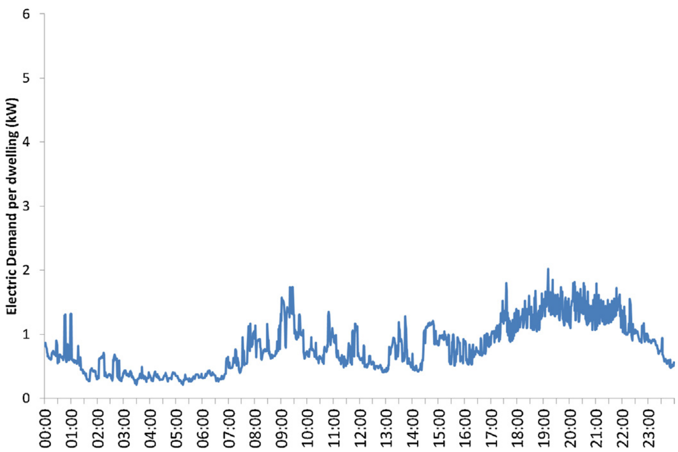

Fig. 4. Minutely electrical demand profile aggregated for nine sample dwellings on December 21st.

be added to this aggregation to demonstrate a more representative and diverse profile.

The final goal of this exercise would be to produce an aggregated profile shape that has the characteristics (such as ADMD and load factor) of, for example, network profiles used by the national grid, but also consists of separate, individual profiles that demonstrate recognisable behaviour and activities that might be expected in a dwelling (and sensitive to time-of-day and seasonal effects).

3. Synthesising demand profiles

3.1. Statistical methods

A range of methods are available in literature for generating statistically duplicate time-series, generally referred as "synthetic time-series". Ideally, these synthetic time-series should exhibit similar spatio-temporal characteristics (stationary, non-stationary or ergodic) as the original series. Similarly, the synthetic series should display similar statistical properties (such as mean, variance, percentiles, distribution) as the original series at any given time *t*. The most commonly used methods for synthesising time-series are: moving average (MA), autoregressive (AR), autoregressive-moving average (ARMA), and autoregressive integrated moving average (ARIMA) models. The first three techniques (MA, AR and ARMA) are more suitable for stationary series, whereas the last one (ARIMA) is specifically applied for non-stationary processes [22]. Other popular time-series modelling techniques include Markov Chain Models, Monte-Carlo Simulation, Methods of Surrogate and Fast Fourier Transform [23,24].

A typical annual electricity demand profile for a building, at minutely resolution, is a complex combination of various deterministic (periodic and aperiodic) and stochastic components, which might be attributed to various factors such as use of electrical appliances, lighting, occupancy/activity pattern and diurnal/seasonal effects. At any given time *t*, these various deterministic and stochastic components can superimpose on each other and thus values in a typical profile corresponds to a non-stationary and highly stochastic process. For example, while a refrigeration cycle can be modelled as a reasonably deterministic process with time, the switching on of a kettle, light, or any other electrical appliance could be a purely random event, albeit with a greater probability of occurrence at certain times of the day. As auto-regressive type models are based on the idea of exploiting various spatial and temporal correlations in an observed series, these types of models are deemed unsuitable for this case. For the purpose of generating synthetic minutely electric demand profiles, this work proposes Hidden-Markov model (HMM) techniques.

As discussed in Section 1, several methods have been proposed for generating electricity demand profiles, but most require additional detailed information on, the household activities, occupancy profiles, appliance switch on-off records, lifestyle, habits, etc., as part of the modelling process [6,11]. With no such prior information available, this article presents a framework for generating synthetic electricity profiles by exploiting various statistical properties of a small number of observed empirical profiles through HMM techniques. As part of this method, a set of 480 distinct HMMs are formulated and integrated through an algorithm developed in R [25] to generate *N* (user specified number) synthetic annual electricity profiles at minutely resolution, which will display similar properties as the original empirical profiles. In this way, a small number of demand profiles can be extrapolated to a much larger number, such that an aggregated, multi-dwelling profile should exhibit smoother and more diverse patterns throughout the day (as demonstrated in Section 4).

HMM provides the ability to account for unobserved (hidden) states in a system, and so is more flexible than conventional Markov modelling of high-resolution data [26]. HMM has many applications, including the generation of synthetic time-series from observed time-series, and has been successfully applied across a range of research areas [27,28]. In general, for a dynamic process, the HMM technique is based on defining a few discrete number of distinct states, with the probability of the system being in a particular state at any given time $(t+1)$ solely dependent on the state of the system at time *t*. There is the allowance for the system to pass through various hidden states while varying between these pre-defined discrete states (which, for this study, would be values of power consumption in kW). Theoretically, HMM is structured into five components: (i) a set of distinct observed states; (ii) a set of unobserved states within these observed states; (iii) a "state transitional probability matrix", defining the probability of transition between different observed states; (iv) an "emission probability matrix", defining probabilities of the unobserved states; and (v) a set of initial probabilities of the observed state.

For modelling electricity load profiles, five distinct states of the system have been defined by dividing the observed values of electricity load (from the nine-dwelling dataset) into five different ranges based on a percentile analysis. For example, state A corresponds to a load between the minimum value and 20th percentile value; state B refers to values between the 20th and 40th percentile; state C refers to the 40th and 60th percentiles; state D refers to the 60th and 80th percentile; and finally state E refers to the 80th percentile and maximum load value. The proposed HMM technique then requires a "state transitional probability matrix" (defining the probability of transition between these specified states of A, B, C, D and E) and an "emission probability matrix" (defining the probabilities of various observed hidden states, up to a resolution of 0.1 kW, within the range of specified states) to initialise the simulation process for generating synthetic electricity profiles. Initial probabilities of the observed states have been estimated from the input dataset.

The use of distinct HMM allows variations across months to be effectively incorporated, such that a synthesised winter and summer profile will look appropriately different. Furthermore, by analysing the empirical profiles, this process is able to identify active and inactive days and hours from the dataset, and replicate these in the synthetic profiles. The algorithm is therefore able to distinguish between a typical weekday (of low afternoon activity) and a typical weekend day (of higher afternoon activity), as well as homes that regularly have someone present during the day (a sign that the occupant is unemployed or retired). The process of distinguishing activity is described in the following steps:

1. For modelling monthly variations, starting from the empirical dataset is divided into six sets by pairing together two consecutive months (from "January-February" to "November-December")
2. Two distinct day types, "active" and "inactive", are defined based on a percentile analysis of the energy demand between 12:00 and 16:00 for both weekdays and weekends (a time period which can be used to signal whether a home is regularly used during the day, though other time periods can be chosen if desired). This percentile analysis focuses on the power spikes during this time, investigating the frequency that 2 kW is exceeded. Should this happen more than six times during this period the day is labelled as "active" (where this threshold value of 6 has been obtained by measuring the 10th percentile value of the number of events when energy demand exceeded 2 kW). This proposed algorithm can be applied with a different time period (than 12:00–16:00), a different value of threshold (than 2 kW) and a different level of percentile cut-off (than 10th percentile) to generate a diverse range of user-specific activity levels and occupancy types.
3. To account for the variations of occupancy and activities, a typical day can be fragmented into various periods. A pre-statistical analysis suggests creating 20 such periods: 4×2 h periods for 00:00 to 08:00, and then 16 periods for each remaining hour of the day.
4. Using the above specified algorithm designed in R, 480 separate HMM models for each time period (i.e. 20 (hour type) $\times$ 2 (weekday type) $\times$ 2 (weekend type) $\times$ 6 (month type) = 480) are integrated together to generate N (user-specified) synthetic annual electricity demand profile at minutely resolution. If it is desirable that the synthesised profiles exhibit a different activity ratio (i.e. number of active to inactive days in a week) to the empirical profiles, then the user simply inputs this ratio to create a range of possible variations in occupancy type (see also Section 3.4).

3.2. Comparison of real with synthetic dwellings

While Section 4 investigates the use of the synthetic profiles for aggregated dwellings, it is important to compare the features of a synthetic dwelling with that of a real dwelling, to test whether the two types of profiles are statistically similar.

Fig. 5 presents typical January and June days which are randomly selected from a synthetic annual profile (generated using the algorithm described in Section 3.1). Comparing these profiles with Figs. 1 and 2 in Section 2.1 shows there is some similarity in the type of features generated. In both synthetic and empirical profiles, the low activity, early morning period (00:00 to 08:00) shows energy use than would be attributed to refrigeration cycles; activities such as cooking and showering are evident in later morning (08:00 to 12:00); and more active evening periods (18:00 to 00:00) can be seen with spikes of demand that would be consistent with cooking and consumer electronics. Furthermore, the seasonal effect of increased natural lighting hours in summer (and therefore reduced electrical lighting) along with higher external temperatures (less electric heating or reduced pump usage of a gas boiler) can be discerned between June and January profiles (particularly during the evening period).

While this slightly subjective, visual inspection is useful as a first indicator of whether the synthetic profiles are replicating reality, a more robust, statistical comparison is required. This can be achieved through a percentile analysis of both empirical and synthetic profiles over time.

Figs. 6 and 7 compare five percentile ranges for real and synthetic profiles measured at each minute of the day for January and June, respectively (across each entire month). The percentile values of the synthetic profiles demonstrate a reasonable agreement with the empirical profiles throughout the day. It is noticeable, however, that the very high values (in the 90th percentile) are slightly more variable across the day for the synthetic profile. In crude terms, the synthetic profiles (as evident from the visual inspection of individual daily profiles) are "spikier" than the empirical profiles, and this occurs during times of high activity (generally associated with meal

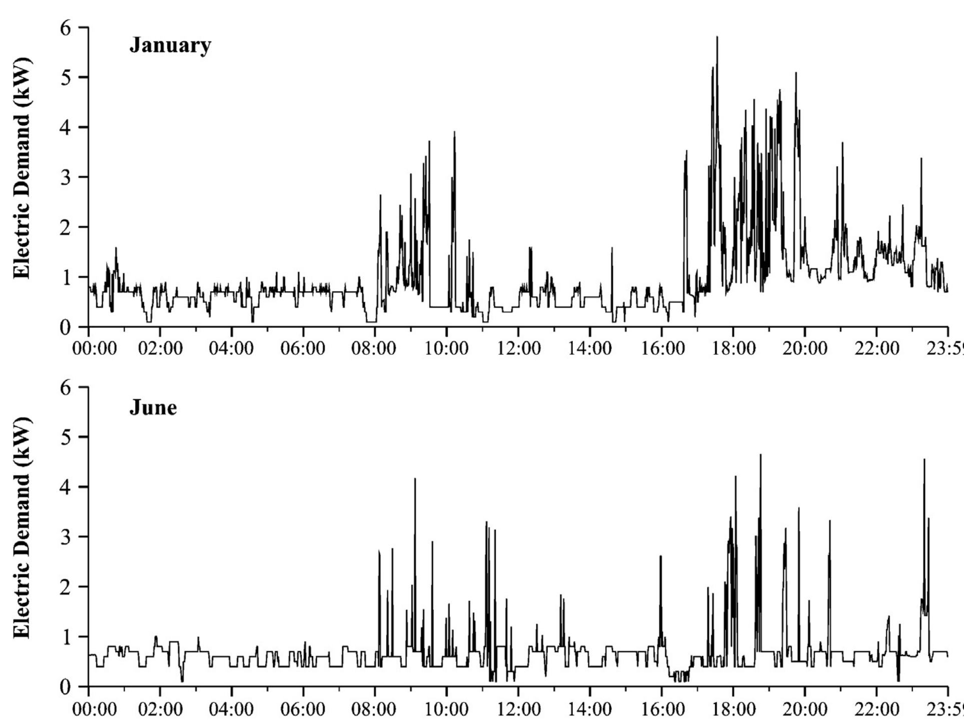

Fig. 5. Minutely electrical demand profile for synthetic dwelling on a randomly selected day in January (upper panel) and June (lower panel).

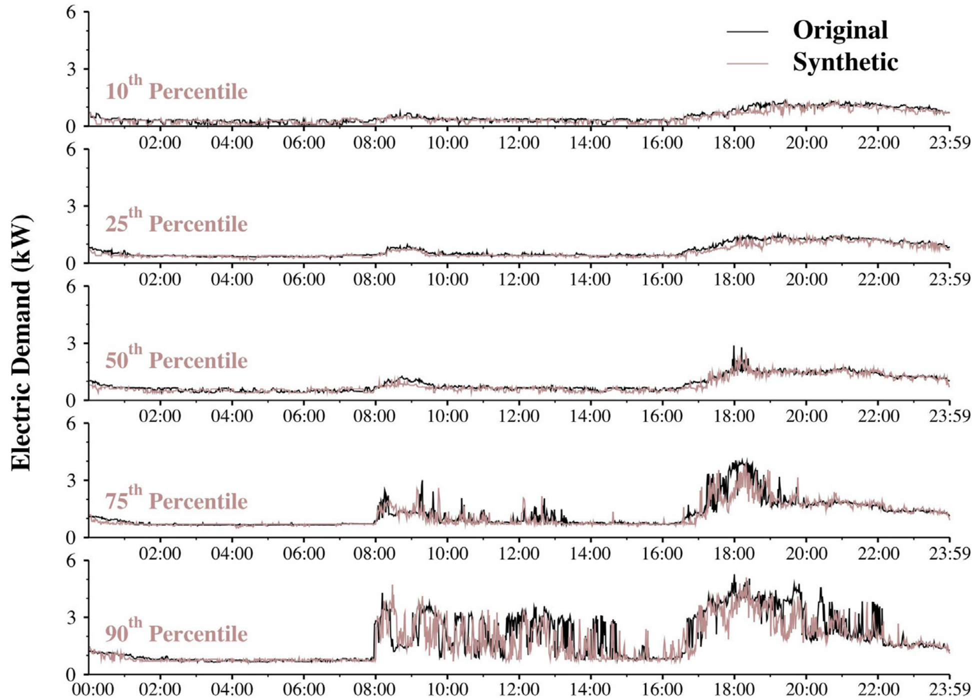

Fig. 6. Five summary statistics compared for one real and corresponding synthetic profile for January.

times). These partly stochastic features, referred to elsewhere as heating element spikes, are very difficult to reliably predict. However, there is still a clear pattern, exhibited by both synthetic and empirical profiles, of a greater frequency of high values at times of higher activity; it is this pattern that is the key to constructing aggregated energy demand profiles of multiple dwellings, where the diversity and fluctuation of energy use at this time needs to be represented.

3.3. Upscaling data through synthesis

The effect of adding profiles of multiple dwellings together in an aggregated profile is shown for one day in Fig. 8. The difference between a single dwelling and just nine different dwellings (based on the empirical dataset) is quite noticeable. However, this nine-dwelling profile still exhibits sharp peaks suggesting that an acceptable level of diversity is yet to be reached. The 45- and

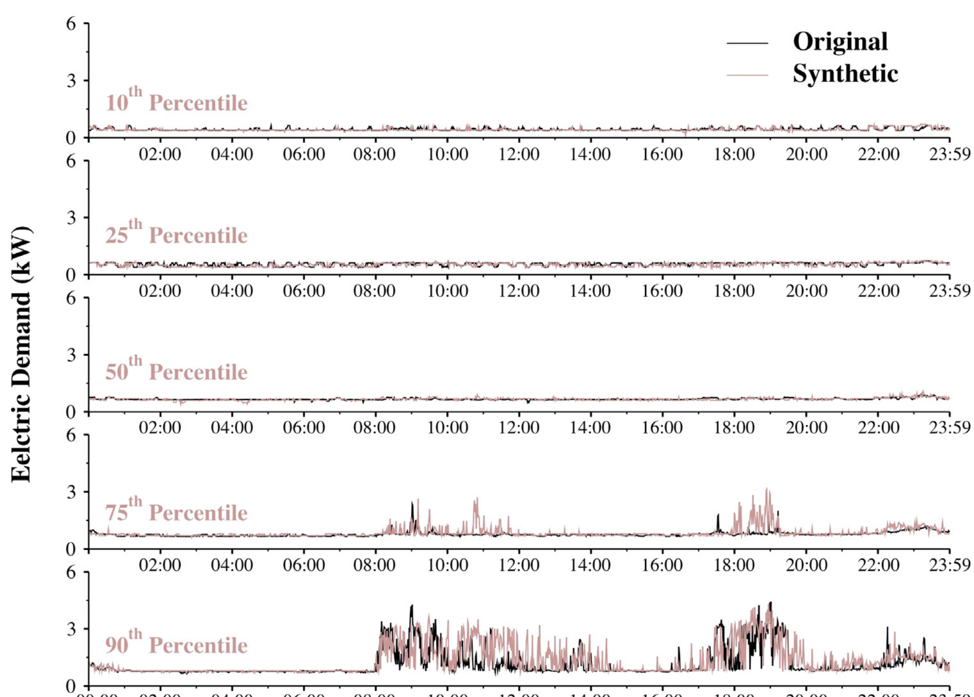

Fig. 7. Five summary statistics compared for one real and corresponding synthetic profile for June.

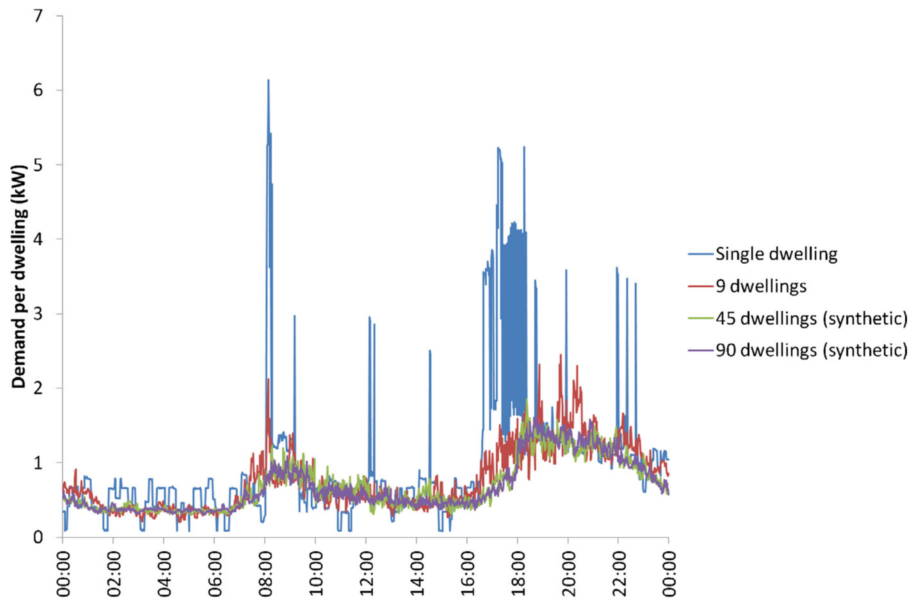

Fig. 8. Comparison of diversity in profiles for single and multi-dwelling datasets for January 17th.

90-dwelling profiles show a pattern that is intuitively consistent with domestic energy patterns throughout the day and, specifically, maps the times of high and low energy consumption in the demand dataset used to generate the data. Due to the scale of the y-axis, some of the smaller features on the 45- and 90-dwelling profiles are not visible, but it is clear that the smoother profiles are tending towards something that might be comparable to demand profiles of large groups of dwellings, such as might be recorded at low-voltage transformer level.

Unfortunately, the database used for this study did not have corresponding transformer level data (e.g. for hundreds of homes). However, with the intention of showing that this synthetic data can be scaled up to something that has similar characteristics to this type of data, Section 4 will demonstrate this using alternative data that was available to the project.

3.4. Morphing for different activities

The described upscaling process has the obvious limitation that it can only replicate the input empirical data, which for this study has been a small sample. The caveat should therefore always be that the aggregated profiles are for dwellings of a similar type and similar behavioural patterns. However, there is some ability to morph the data beyond the original dataset, particularly in terms of occupancy patterns. This is possible due to the nature of the extrapolation process (in Section 3.1) which identifies “active” and “inactive” days from the frequency of high power features in the data. This can indicate dwellings that have a working household during a weekday (i.e. high probability that no occupants are present during 9 am to 5 pm) or someone who is unemployed and therefore present during the day (although it is not possible to identify the number of occupants present). The synthetic algorithm can, if requested, produce a different balance between active and inactive days for the synthetic profiles. For example, in Fig. 8, the 90-dwelling profile could be re-configured to represent households with higher unemployment than the empirical, 9-dwelling database. If using the algorithm for future demand projections, this could similarly be used to investigate the effect of increased home-working.

4. Demonstration of synthesised profiles

Part of the stimulus behind the formulation of the algorithm is to convert small datasets into larger, usable datasets. This section will discuss some possible applications of the algorithm along with the type of output generated, with a comparison with real data.

4.1. Comparing diversity with real substation data

To understand typical electrical demand profile shapes for larger groups of dwellings, low-voltage substation data was obtained from a different site (in Cheshire, linked to the Ashton Hayes project [29]) to that of the individual dwelling database. The substation data was also more recent than the individual data, and the efficiency and power profiles of household appliances are likely to be significantly different. As well as being for 230 dwellings (served by the substation, with negligible non-domestic properties within the network), the substation data is also at a 10-minute resolution so will naturally appear smoother than the minutely synthetic profile. To improve the comparison, the 90-dwelling synthetic profile (of Fig. 8) is further upscaled to 225 dwellings (with the algorithm working in multiples of 9, due to the size of the empirical dataset). Figs. 9 and 10 compare this 225-dwelling synthetic aggregated profile with this substation data – though, as clarified, this comparison is to understand approximate profile shapes rather than being used as an accurate validation of the model. The chosen winter day of Fig. 9 shows an excellent match between the two profiles until 6 pm. At this point, the 225-dwelling profile might betray less efficient lighting technology, as this is the time during a working winter day that lighting would be more evident; due to the age of the data it would be a reasonable estimate that most lighting in the individual dwelling dataset is incandescent lighting, whereas the substation data is likely to include dwellings with a higher proportion of low energy lighting.

The comparison between the summer profiles in Fig. 10 is less satisfactory, but the synthetic profile still demonstrates a less variable summer demand than winter, with some features evident in both synthetic and substation profiles (such as post-10 pm decline in demand and steep gradient in the morning). While it is impossible to accurately identify reasons for the deviation between the

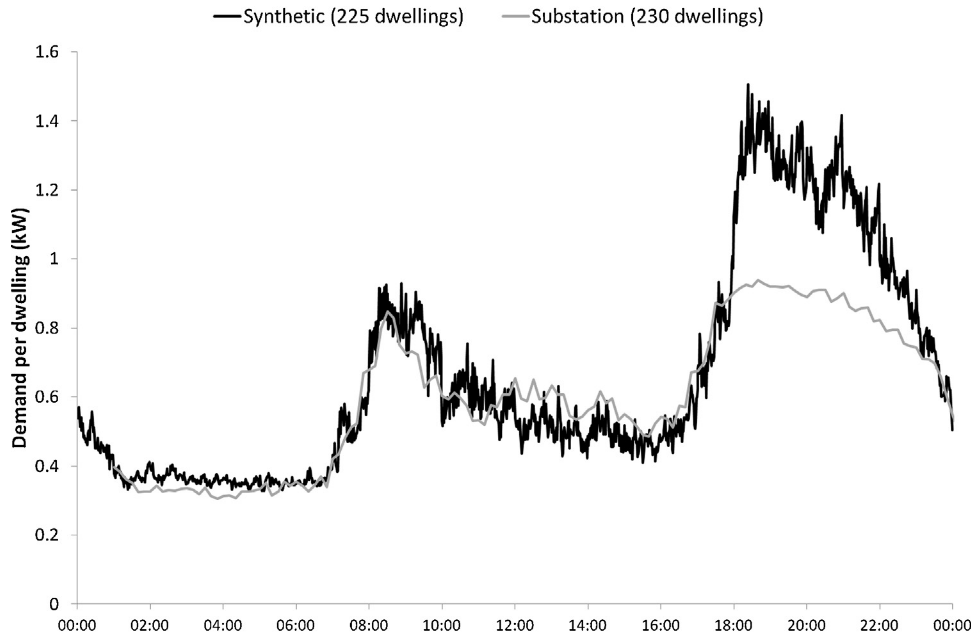

Fig. 9. Comparison of diversity in profiles for 90 synthetic homes and 230-dwelling substation data for January 17th.

two profile types, differences in refrigeration technologies might be seen in the early morning (prior to the rising gradient). A less efficient refrigeration technology will be consuming more power, which would be more evident in the summer profile (e.g. due to poorer insulation), and if this was the case then the synthetic data (based on older technology) would show high values of power demand in the morning during low or no activity.

This is, however, largely conjectural and it is therefore not possible to use this data as a robust validation exercise. A slightly broader picture can be obtained by comparing the profiles from across the entire year, as demonstrated in Figs. 11 and 12. The substation data in Fig. 11 again shows some similar features to that of the synthetic data in Fig. 12, with conclusions about the comparison broadly similar to those outlined above.

4.2. Application of method

The ARIES project is currently continuing with this model validation exercise and attempting to obtain data to extend this analysis, including for non-domestic buildings. Ultimately, the goal is to have a robust and flexible method to project daily demand profiles for future climate and technology scenarios. Part of this approach includes a method for filtering the demand data based on the shape of the individual dwelling profiles (which would work on both synthetic and empirical data). These filters, detailed elsewhere [30], would be applied to every individual dwelling in an automated way such that the final aggregated profile can show different types of energy consumption within that profile. The worked example of Fig. 13 shows filtered standby (relating to continuous

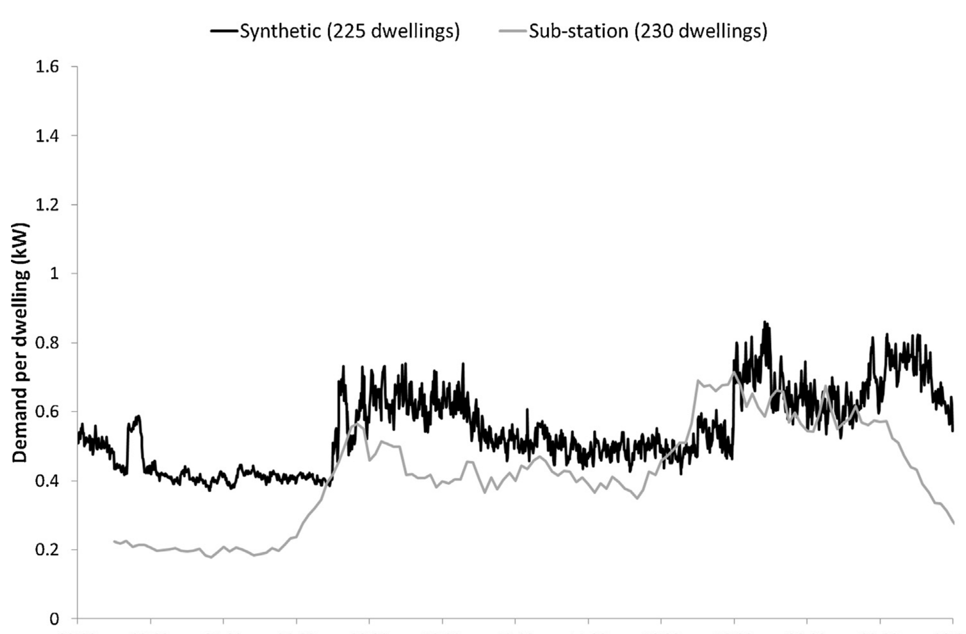

Fig. 10. Comparison of diversity in profiles for 90 synthetic homes and 230-dwelling substation data for June 13th.

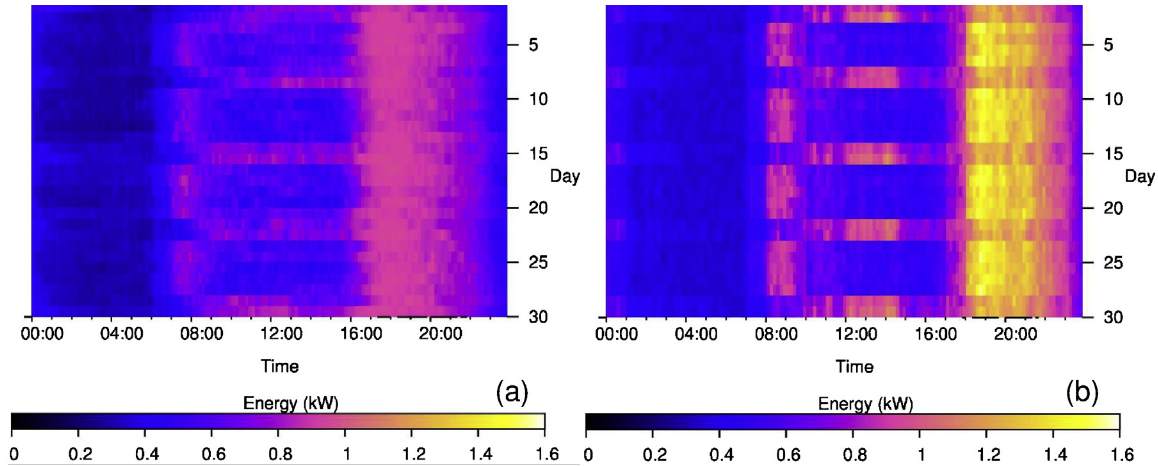

Fig. 11. Comparison of January monthly profiles for (a) substation data and (b) synthesised equivalent.

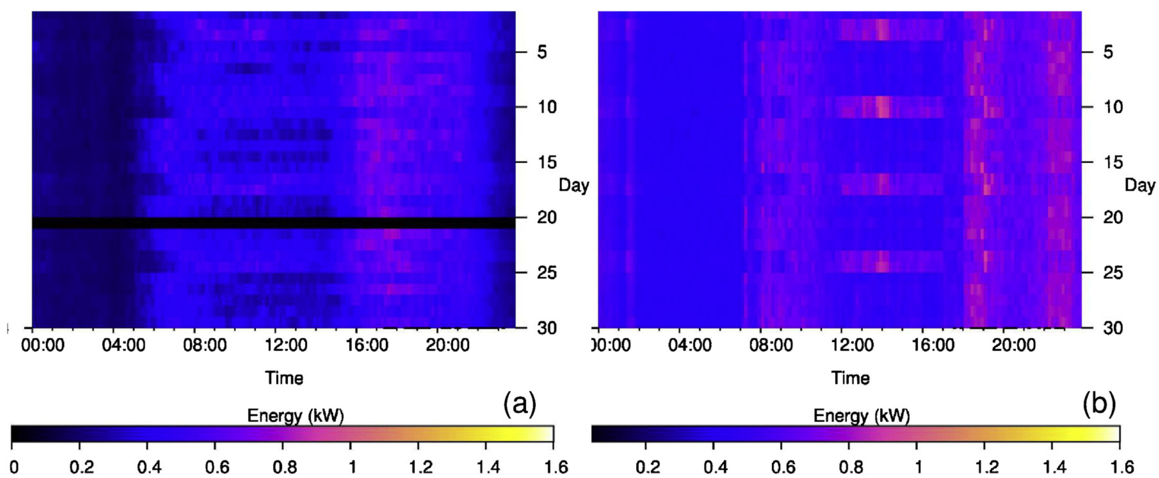

Fig. 12. Comparison of June monthly profiles for (a) substation data and (b) synthesised equivalent (NB. The black horizontal line at day 20 refers to missing data).

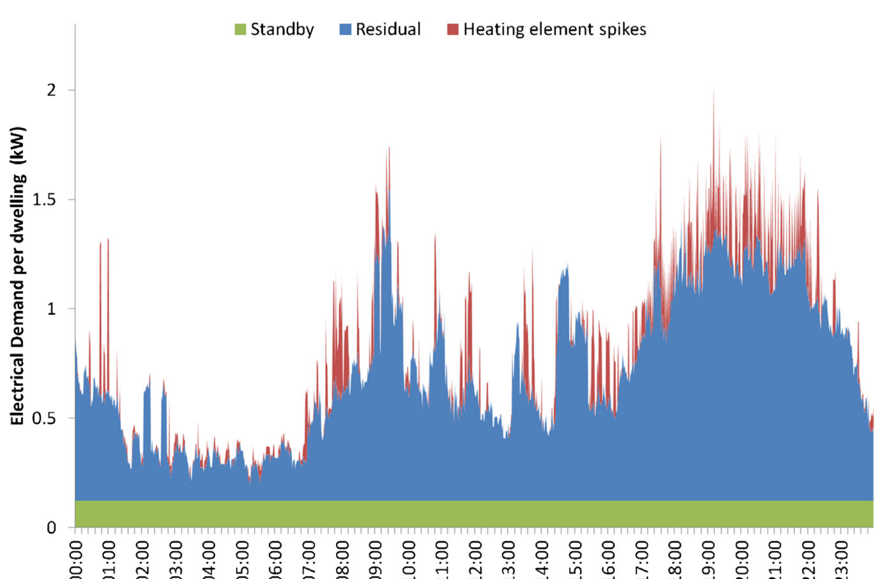

Fig. 13. Categorised energy use of nine dwellings after filtering (December 21st).

demand identified throughout day), heating element spikes (usually associated with cooking appliances and electric showers) and residual (remaining demand from lighting and consumer electronics) energy demand. These filters are currently being refined and applied to larger datasets.

This can be invaluable when attempting to morph the profiles for future technology – the filters allow us to see what type of energy is being used at different times, and thus make a judgement about how this might change for some future scenario. While it is not possible to distinguish between individual appliances in an automated way, the filters can suggest when a technology change might have maximum impact, rather than having to assume an averaged reduction in energy consumption across the entire day.

Ultimately, the morphed future demand profiles, based on the synthetic generation described above, will be compared to the energy supply options that might be available in future as the UK attempts to meet targets for renewable energy production.

5. Conclusions

Domestic electrical demand profiles, at appropriate resolution, display features and characteristics that can provide an indication of types of energy use in the home. However, the information provided by a single dwelling profile is significantly different to that of an aggregated multi-dwelling profile, but it is the latter that can allow us to make more general extrapolations as to how future technologies (and climate) might affect energy patterns in the UK. Providing a synthesis algorithm that, by generating multiple single-dwelling profiles, provides a bridge between these two scales of profile could allow wider applications for relatively small (in terms of households) datasets.

There is still a limit to this extrapolation but the current approach does allow for the creation of a diverse, aggregated profile that can then be morphed by altering the original individual demand profiles (using filters, as discussed). It can also be used to explore how size and shape of profiles affect ADMD profiles; for example, investigating if future technology might result in a more variable demand profile (with a lower load factor). Estimating this change can be useful for designing supply-side options, such as understanding the required versatility for relatively new (e.g. renewables) technologies (or, at least, new scales of reliance on these technologies).

The synthetic profiling method is currently undergoing further validation within the ARIES project and also the application for non-domestic building demand profiles will be investigated. As part of this validation, larger datasets are being sought with associated low-voltage transformer loads from networks that are actually serving those same buildings. This will provide a more robust test of the described demand synthesis algorithm, and allow for greater confidence in its further application.

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