Energy & Buildings 179 (2018) 292–300

Contents lists available at ScienceDirect

Energy & Buildings

journal homepage: www.elsevier.com/locate/enbuild

Seasonal variation in household electricity demand: A comparison of monitored and synthetic daily load profiles

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ARTICLE INFO

Article history:
Received 6 June 2018
Revised 23 August 2018
Accepted 10 September 2018
Available online 21 September 2018

Keywords:
Domestic electricity demand
Electricity demand modelling
Electricity load profiles
Seasonality
English homes

ABSTRACT

This paper examines seasonal variation in household electricity demand through analysis of two sets of half-hourly electricity demand data: a monitored dataset gathered from 58 English households between July and December 2011; and a synthetic dataset generated using a time-of-use-based load modelling tool. Analysis of variance (ANOVA) tests were used to identify statistically significant between-months differences in four metrics describing the shape of household-level daily load profiles: mean electrical load; peak load; load factor; and timing of peak load. For the monitored dataset, all four metrics exhibited significant monthly variation. With the exception of peak load time, significant between-months differences were also present for all metrics calculated for the synthetic dataset. However, monthly variability was generally under-represented in the synthetic data, and the predicted between-months differences in load factors and peak load timing were inconsistent with those exhibited by the monitored data. The study demonstrates that the shapes of household daily electrical load profiles can vary significantly between months, and that limited treatment of seasonal variation in load modelling can lead to inaccurate predictions of its effects.

1. Introduction

In passing the 2008 Climate Change Act, the UK government committed to achieving an 80% reduction in greenhouse gas (GHG) emissions by 2050, compared with a 1990 baseline [19]. The domestic sector is identified as a significant target for emissions reductions, having accounted for 28% of UK final energy use in 2016 [4], and 23% of GHG emissions in 2015 [3]. The UK Carbon Plan identifies the replacement of fossil fuels with low-carbon and renewable generation as key to achieving emissions reductions [20], and the UK Renewable Energy Roadmap sets a target of 15% of UK energy being derived from renewables by 2020 [13].

2017 projections estimate that renewable generation will account for 45% of the UK electricity market by 2035, with nuclear generation accounting for a further 34% [5]. In 2016, solar photovoltaic (PV) and wind generation facilities accounted for 55% of UK renewable energy generation, and represented 48% of the national installed renewable electricity generation capacity [4]. However, the UK solar and wind resources are prone to diurnal and seasonal variability [8,29], while nuclear plants typically run at constant power and therefore provide limited flexibility in comparison with fossil fuels [33].

The changing complexion of the UK electricity supply will present new challenges in demand-supply balancing: mismatches are likely to arise between times of peak renewable generation and peak demand, and the inflexibility of nuclear power renders it unable to efficiently satisfy peak loads. There is therefore a growing need to understand and predict the time-varying behaviour of electricity demand—on diurnal and seasonal timescales—in order to determine the scale and timing of loads that will need to be satisfied by flexible backup generation or energy storage technologies.

Studies exploring relationships between household characteristics and overall electricity demand are widely reported in the academic literature [21]; however, relatively few evidence-based studies have been conducted to establish the factors influencing the shape of daily load profiles [25]. UK studies have tended to be restricted to small samples or limited monitoring periods [10,40], and seasonal variability in diurnal demand patterns has yet to be rigorously analysed.

Previously reported load profile modelling exercises have similarly been lacking in rigorous treatment of seasonal variation in load profile shapes: validation of seasonal variation, for example, has tended to focus only on overall energy demand and superficial comparisons of mean daily load profiles [23,32,36]. However, it has been noted that day of the week and the time of

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https://doi.org/10.1016/j.enbuild.2018.09.018

year both influence the shape of household-level daily load profiles [16,36], and recently reported appliance-level load-profiling models demonstrate a growing tradition of justifying treatment of seasonal variation through rigorous analyses of monitored electricity demand data [37,39].

The objectives of this paper are: (i) to illustrate the significance of the effects of seasonality on household daily electricity load profiles; and (ii) to examine the representation of those effects in synthetic load data. The analysis focuses on a pair of half-hourly dwelling-level electricity demand datasets, similar to the type expected to be provided by smart meters [14]: the first derived from data gathered in 58 English households during the 2011 Energy Follow-Up Survey (EFUS) [12,15]; the second a set of synthetic load profiles generated using a stochastic load profiling tool developed by Richardson and Thomson [35]. Four electricity demand metrics are used to describe household-level load profiles, and the effects of seasonal variability are investigated through statistical analysis of metrics calculated from monthly data.

2. Materials and methods

2.1. Monitored load profiles: The EFUS dataset

The monitored load profiles analysed for this paper were gathered during the Energy Follow-Up Survey (EFUS) of 2011, commissioned by the Department of Energy and Climate Change (DECC) to collect data on domestic energy use in England [12]. The EFUS sample consisted of 2616 households drawn from participants in the 2010/2011 English Housing Survey (EHS), commissioned by the Department for Communities and Local Government (DCLG) to collect data regarding the condition and energy-efficiency of the UK domestic stock [11].

Household-level electricity demand data, recorded at 10-second intervals using digital voltage loggers, were available for 79 of the EFUS households. Prior to the installation of monitoring equipment, householders were interviewed on a range of topics, including household make-up, dwelling characteristics and appliance ownership. Sampling of households was structured to ensure geographic spread of monitor placement across England, with households excluded on the basis of the following criteria [12]:

1. Households in flats;
2. Use of electric mains heating and/or supplementary electric heating;
3. Use of electric water heating;
4. Use of electric heating in conservatories;
5. Absence of mains electricity;
6. Presence of antiquated power sockets and/or consumer units;
7. Inaccessible meter cupboards and/or electrical hazards identified.

Individual household monitoring periods commenced between March and August 2011, and concluded in January 2012. For this paper, the sample was reduced to 62 households—all living in houses—monitored continuously between 1 July and 31 December 2011, such as to allow investigation of monthly variation in a consistent set of households. This was further reduced to 58 households—hereafter referred to as the EFUS58 sample—following the removal of households presenting anomalous load profiles, such as abnormally high overnight loads in summer (perhaps indicating air-conditioning) or long periods of near-zero electricity demand (perhaps indicating an unoccupied dwelling or prolonged monitoring error).

To enable investigation of seasonal variation, this study initially sought publicly available half-hourly electricity demand data gathered over periods of a year or more; however, suitable datasets were sparse. Data from the Energy Demand Research Project (EDRP)—gathered over a period of 2.5 years during early smart metering trials in the UK [1]—were considered; however, the EDRP dataset lacked sufficiently detailed household appliance data required for the definition of synthetic households in the load profile generation exercise described in Section 2.2, and thus the EFUS dataset was preferred.

2.2. Synthetic load profiles: The CREST dataset

The synthetic load profiles analysed for this paper were generated using a bottom-up household electricity demand modelling tool developed by Richardson and Thomson [35] at the Loughborough University Centre for Renewable Energy Systems Technology (CREST)—hereafter referred to as the CREST model—and accessed through the Loughborough University institutional repository [34]. The model provides simulation of household-level demand at a 1-minute resolution, with simulation of occupant activity and appliance use based on data from the 2000 UK Time Use Survey (TUS) [36].

Occupancy modelling in Richardson and Thomson's model is governed by a set of activity profiles, which account for the number of occupants and whether a weekday or weekend day is being simulated. However, the same activity profiles are used regardless of the month being simulated: seasonal variation is accounted for only in modelling of lighting demands, a process dependent on simulation of daily outdoor irradiance profiles. Subsequent comparison of seasonal variations in the monitored and synthetic datasets was therefore expected to indicate potential shortcomings of this limited treatment of seasonality.

Generation of a set of synthetic load profiles comparable with the monitored profiles required the definition of 58 synthetic households matched against the EFUS58 households where possible:

1. Household size was estimated on the basis of EHS-derived statistics associating number of bedrooms with number of occupants [11] (as the EFUS interview data did not include the number of occupants in each household);
2. EFUS interview data [15] were used to match cold appliances, televisions, wet appliances and electric cooking appliances (ovens, hobs, microwaves);
3. Consumer electronics and ITC appliances—data for which were unavailable—were randomly assigned by the CREST model, as were lighting configurations;
4. Simulation of electric water and space heating—which were reported absent across the EFUS58 sample in the EFUS interview data—was disabled.

For each synthetic household, daily load profiles were then generated for the 184 days from 1 July to 31 December 2011, matching the monitoring period of the EFUS58 dataset.

With the exception of televisions, the EFUS interview data did not record numbers of appliances found in each household, only whether each appliance type was present. In defining synthetic dwellings for this study, it was assumed that no household owned more than one of each type of electrical appliance modelled, with the exception of an allowance for up to three televisions per household. Furthermore, as the CREST tool had an upper limit of 5 occupants per dwelling, this was the maximum occupancy modelled.

2.3. Electricity demand metrics

This paper reports on the monthly variability of four per-household electricity demand metrics selected to describe the shapes of household daily load profiles:

1. Mean electrical load L_M;

2. Mean daily peak load L_P;
3. Mean daily load factor L_F;
4. Modal daily peak load time T_P;

The calculation of these metrics was adopted following McLoughlin et al. [24], in which similar metrics were used to characterise domestic load profiles in Irish homes. The metrics are defined in Eqs. (1)–(4), in which $L_{i,j}$ represents a single household's mean electrical load (in kW) for the jth half-hour on the ith day, and n represents the number of days under consideration. While the monitored and synthetic datasets offered data at 10-s and 1-min resolutions, respectively, the decision to re-sample at a 30-min resolution was taken such that the subsequent analyses could be repeated on half-hourly smart meter data in future studies.

Eq. (1) shows mean electrical load L_M, the mean electrical power demand experienced during the n days considered, in kW.

$$L_M = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{1}{48}\sum_{j=1}^{48}L_{i,j}\right) \text{ (kW)} \tag{1}$$

Eq. (2) shows mean daily peak load L_P, the maximum 30-min household load experienced on each day, averaged over the number of days n, in kW.

$$L_P = \frac{1}{n}\sum_{i=1}^{n}\max_{1\le j\le 48} L_{i,j} \text{ (kW)} \tag{2}$$

Eq. (3) shows mean daily load factor L_F, the ratio of daily mean load to daily maximum load on each day, averaged over the number of days n. Load factors are described by McLoughlin et al. [24] as an indicator of the "peakiness" of a load profile: higher load factors generally indicate more consistent demand throughout the day, while lower load factors are indicative of profiles with tall and narrow peaks.

$$L_F = \frac{1}{n}\sum_{i=1}^{n}\frac{\frac{1}{48}\sum_{j=1}^{48}L_{i,j}}{\max_{1\le j\le 48} L_{i,j}} \times 100 \text{ (\%)} \tag{3}$$

Eq. (4) shows modal time of peak load T_P, the half-hour interval most frequently producing the maximum daily load during the n days under consideration. T_P takes integer values between 1 and 48 corresponding to half-hour intervals throughout the day (1 = 00:00–00:30, 2 = 00:30–01:00, …, 48 = 23:30–24:00).

$$T_P = \text{mode}\left\{ j_{max} \middle| L_{i,j_{max}} = \max_{1\le j\le 48} L_{i,j},\ 1 \le i \le n \right\} \text{ (half-hour)} \tag{4}$$

For each of the monitored and synthetic households, the four metrics were calculated using load data corresponding to: (i) each individual month within the 6-month study period (July–December 2011), resulting in a total of 4 metrics/month × 6 months = 24 metrics per household; and (ii) the entire 6-month period.

Additional metrics describing mean base load and mean night-time demand were considered. The former exhibited no significant monthly variability, while the latter exhibited behaviour largely mirroring that of mean electrical load L_M; thus neither metric is reported in this paper.

2.4. ANOVA tests for significant monthly differences

One-way within-subjects analysis of variance (ANOVA) tests were conducted on each of the monitored metrics to identify significant between-months variations in the EFUS monitored load profiles. The within-subjects factor was the monitoring month, and had six levels (July to December). Where the ANOVA tests indicated significant effects, post hoc analyses were applied, with a Bonferroni correction, to identify the pairs of months between which significant differences were present. A 2-tailed significance level of $\alpha = 0.05$ was applied in all tests.

Before proceeding with the ANOVA tests, it was necessary to check whether the monthly metrics were approximately normally distributed [28]: mean electrical load L_M and mean daily peak load L_P both exhibited strong positive skew, and were thus log-transformed to obtain approximately normal distributions[1] Mauchly's test of sphericity was significant ($p \le 0.05$) for all four metrics, necessitating the application of the Greenhouse-Geisser correction to account for failure to satisfy sphericity assumptions [7].

To determine the extent to which monthly variations in the monitored metrics were reproduced in the synthetic metrics, the ANOVA tests and post hoc analyses were repeated on the synthetic metrics. Although all four synthetic metrics were approximately normally distributed, mean electrical load L_M and daily peak load L_P were again log-transformed to allow direct comparison with ANOVA results for the monitored metrics. The Greenhouse-Geisser correction was not applied, as Mauchly's test of sphericity was not significant for any of the synthetic metrics.

3. Results

3.1. Distributions of electricity demand metrics

For each of the monitored and synthetic households, electricity demand metrics were calculated for each month of load data, as per Eqs. (1)–(4), as well as for the whole 6-month dataset. Table 1 compares descriptive statistics for the per-household metrics calculated from the two 6-month datasets, while Figs. 1–4 show the distributions (in boxplot form) of the metrics categorised by month. It should be noted that outliers—data points more than 1.5 interquartile ranges below the first quartile or above the third quartile—have been omitted from these boxplots.

For all four metrics, between-households variability was underestimated in the synthetic data, as shown by smaller standard deviations and maximum–minimum differences for the synthetic metrics compared with monitored metrics (Table 1). The underestimation of between-households variability is also evident in the monthly boxplots (Figs. 1–4), in which the whiskers for the synthetic metrics are consistently shorter than those for the monitored metrics.

3.1.1. Mean electrical load L_M

On average, mean electrical load was underestimated by 26% in the synthetic data compared with the monitored data (Table 1). Furthermore, the comparison of monthly boxplots for monitored and synthetic mean electrical load in Fig. 1 shows that mean load was underestimated in each of the six months from July to December.

Both monitored and synthetic mean electrical load exhibited upward monthly trends from July to December, with the exception of a drop in monitored mean load moving from July to August. Monthly increases were underestimated in the synthetic data: on average, per-household synthetic electrical load increased by 0.013 kW per month, compared with an average increase of 0.032 kW per month for the monitored metric.

[1] Normal approximation was deemed acceptable when |skew| < 1 [27] and |kurtosis| < 2 [17].

Table 1
Descriptive statistics for per-household electricity demand metrics for monitored and synthetic households (6-month datasets, July–December 2011).

Metric / Dataset	*N*	Mean	Median	Standard deviation	Minimum	Maximum
Mean daily electrical load L_M (kW)						
Monitored	58	0.53	0.45	0.35	0.12	2.13
Synthetic	58	0.39	0.40	0.08	0.23	0.57
		(-26%)	(-10%)	(-76%)	(+89%)	(-73%)
Mean daily peak load L_P (kW)						
Monitored	58	1.91	1.76	0.90	0.62	5.45
Synthetic	58	2.00	2.02	0.41	1.22	2.71
		(+5%)	(+14%)	(-54%)	(+97%)	(-50%)
Mean daily load factor L_F (%)						
Monitored	58	30.21	29.57	6.14	18.43	46.30
Synthetic	58	21.24	21.08	2.31	16.09	28.88
		(-30%)	(-29%)	(-62%)	(-13%)	(-38%)
Modal daily peak load time T_P (HH)[a]						
Monitored	58	32.50	35.00	8.22	15.00	45.00
Synthetic	58	37.72	38.50	6.72	18.00	45.00
		(+16%)	(+10%)	(-18%)	(+20%)	(+0%)

[a]Half-hour: 1 = 00:00 to 00:30, ... , 48 = 23:30 to 24:00.
Values in parantheses indicate percentage difference between synthetic and monitored statistics.

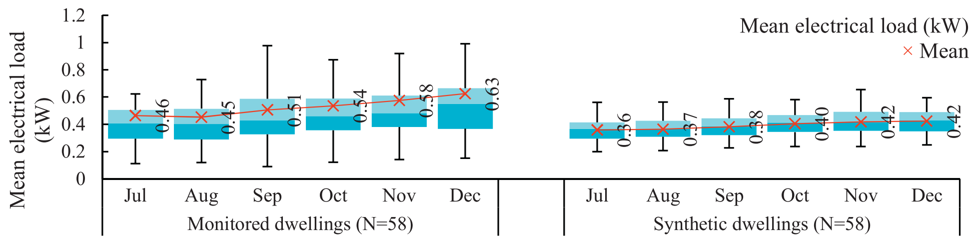

Fig. 1. Boxplots of per-household mean electrical load L_M (kW) for monitored households compared with synthetic households (July–December 2011). Ends of whiskers indicate minimum and maximum values within 1.5 × IQR of the lower and upper quartiles, respectively.

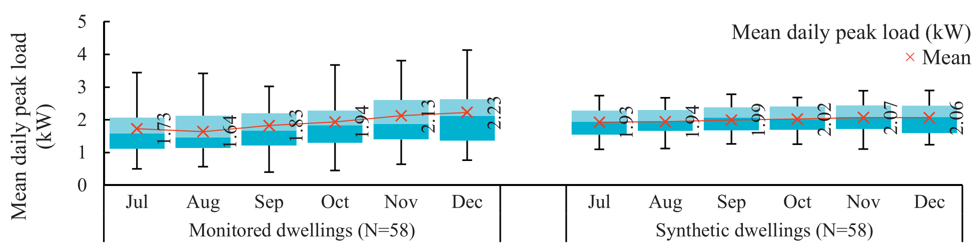

Fig. 2. Boxplots of per-household mean daily peak load L_P (kW) for monitored households compared with synthetic households (July–December 2011). Ends of whiskers indicate minimum and maximum values within 1.5 × IQR of the lower and upper quartiles, respectively.

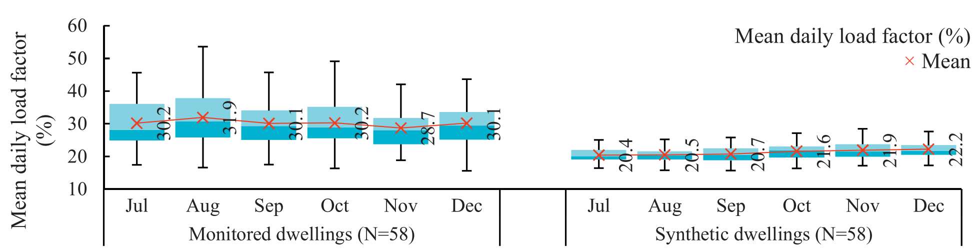

Fig. 3. Boxplots of per-household mean daily load factor L_F (%) for monitored households compared with synthetic households (July–December 2011). Ends of whiskers indicate minimum and maximum values within 1.5 × IQR of the lower and upper quartiles, respectively.

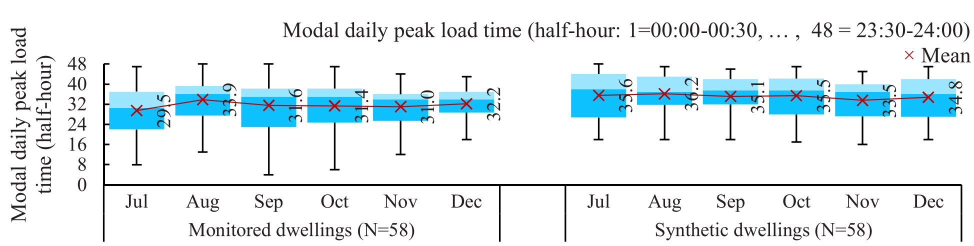

Fig. 4. Boxplots of per-household modal daily peak load time T_P (half-hour) for monitored households compared with synthetic households (July–December 2011). Ends of whiskers indicate minimum and maximum values within 1.5 × IQR of the lower and upper quartiles, respectively.

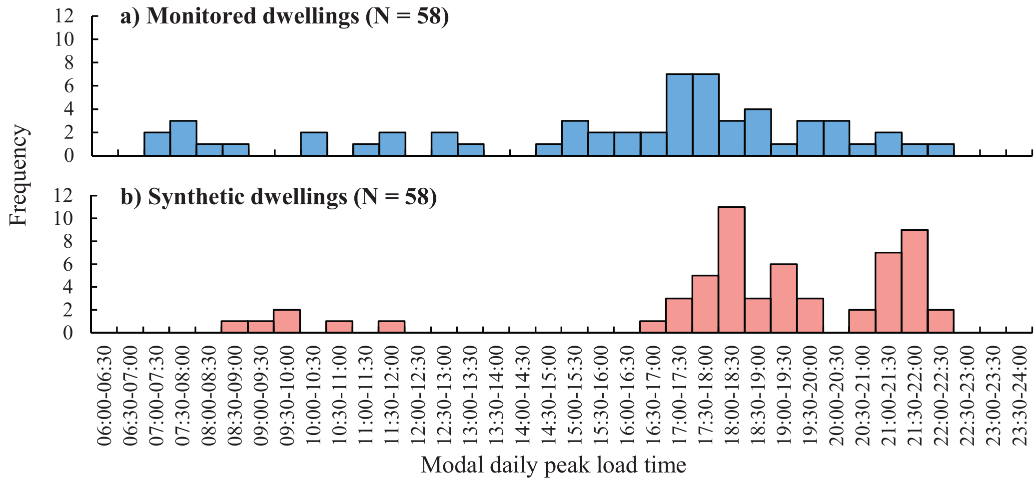

Fig. 5. Distribution of per-household modal daily peak load time T_P for monitored dwellings compared with synthetic dwellings (6-month datasets, July–December 2011).

3.1.2. Mean daily peak load L_P

Mean daily peak load L_P was, on average, overestimated by 5% in the synthetic data compared with the monitored data (Table 1). Comparing monthly boxplots for monitored and synthetic mean daily peak loads (Fig. 2), it can be seen that peak loads were overestimated for each month from July to October, but underestimated for November and December.

Monitored and synthetic mean daily peak load both exhibited upward monthly trends from July to December, again with the exception of a slight fall in the monitored metric between July and August. Monthly increases were again underestimated in the monthly synthetic data: on average, per-household synthetic daily peak loads increased by only 0.026 kW per month in comparison with an average monthly increase of 0.10 kW for the monitored metric.

3.1.3. Mean daily load factor L_F

On average, mean daily load factor L_F was underestimated by 30% (in absolute terms) in the synthetic data (Table 1) compared with the monitored data; comparison of monthly boxplots shows that load factors were also underestimated in each individual month. This indicates that the monitored households exhibited less "peaky" load profiles than the synthetic households.

Synthetic mean load factor L_F exhibited a clear upward monthly trend (Fig. 3). As the operation of the CREST model accounted for no seasonal variation other than changing lighting demands, this trend can be attributed to the impact of increasing lighting loads moving into the winter months. In contrast, no clear monthly trend emerged in monitored load factors, although August appeared to present higher load factors.

3.1.4. Modal daily peak load time T_P

Synthetic modal daily peak load times were, on average, 5.2 hours later than monitored peak load times (Table 1). Comparing the distributions of modal daily peak load times (Fig. 5), it is evident that the synthetic data under-predicted the occurrence of morning and daytime peaks: while 23 of 58 monitored dwellings had a modal peak load time earlier than 16:30, only 6 of 58 synthetic dwellings reported a modal peak load time before 16:30. Furthermore, there was an over-prediction of late-evening peak load times: while only 5 monitored households presented modal peak load times between 20:30 and 22:30, 20 synthetic households had modal peak load times in the same interval. Both of these differences contributed to the comparatively later mean synthetic peak load time when compared with mean monitored peak load time.

The comparison of monthly distributions for monitored and synthetic peak load times in Fig. 4 shows that synthetic peak load times were, on average, later than the monitored load times in each individual month. Mean monitored and synthetic peak load times were both latest in August, but no clear month-on-month trend emerged in either dataset.

3.2. Significance of monthly differences

The results of one-way within-subjects ANOVA tests, conducted separately on monitored and synthetic electricity demand metrics to identify significant monthly differences, are shown in Table 2. The significance of monthly differences is shown by p values, with significance noted at the $\alpha = 0.05$ and $\alpha = 0.01$ significance levels. As noted in Section 2.4, log-transformations were applied to mean load L_M and peak load L_P in order to satisfy normality assumptions, and Greenhouse-Geisser corrections were applied to the monitored metrics to account for their failure to satisfy sphericity assumptions.

The results of Bonferroni-corrected post hoc analyses are visualised in Figs. 6–9 using 95% within-subjects confidence intervals. These intervals were constructed using a Cousineau-Morey approach, as recommended by Baguley [2] for visual representation of ANOVA test results: non-coincident confidence intervals indicate a significant between-months difference at the $\alpha = 0.05$ significance level. It is noted that these intervals only indicate the significance of between-months differences within each individual set of metrics, monitored and synthetic; they do not indicate the significance of differences between the monitored and synthetic metrics.

The results of the ANOVA tests (Table 2) showed that there were significant between-months differences for all four monitored metrics, and also for three synthetic metrics: log-transformed mean electrical load $\log L_M$, log-transformed mean daily peak load $\log L_P$, and mean daily load factor L_F. Effect sizes, as indicated by partial η^2 values, indicate the proportion of variance in the metrics that can be attributed to monthly classification. Smaller effect sizes for monitored mean electrical load and mean daily load factor, when compared with the synthetic equivalents, indicate that the greater variability observed in the monitored metrics (Table 1, Figs. 1 and 3) is due to the influence of factors other than between-months variability in lighting demand embodied in the CREST model.

3.2.1. Mean electrical load L_M

For mean electrical load L_M, the results of post hoc analyses using the Bonferroni correction (visualised in Fig. 6) indicated that

Table 2
Results of one-way within-subjects ANOVA tests for significant monthly differences in monitored and synthetic electricity demand metrics.

Metric	df1	df2	F-statistic	p-value	Partial η^2 (effect size)[a]
Monitored					
Log mean electrical load $\log L_M$	3.11	177.17	38.983	$<$ 0.0005**	0.406 (large)
Log mean daily peak load $\log L_P$	3.40	193.87	32.186	$<$ 0.0005**	0.361 (large)
Mean daily load factor L_F	3.92	223.45	4.012	0.004**	0.066 (medium)
Modal daily peak load time T_P	4.09	233.01	2.519	0.041*	0.042 (small)
Synthetic					
Log mean electrical load $\log L_M$	5	285	85.958	$<$ 0.0005**	0.601 (large)
Log mean daily peak load $\log L_P$	5	285	11.160	$<$ 0.0005**	0.164 (large)
Mean daily load factor L_F	5	285	27.284	$<$ 0.0005**	0.324 (large)
Modal daily peak load time T_P	5	285	0.690	0.631	0.012 (small)

* Significant at the 0.05 level (2-tailed). ** Significant at the 0.01 level (2-tailed). [a]Classification of effect sizes follows Cohen's [9] benchmark partial η^2 values of .0099, .0588, .1379 for small, medium and large effect sizes.

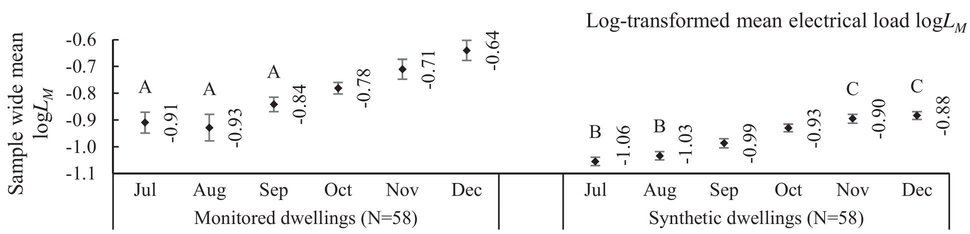

Fig. 6. 95% within-subjects confidence intervals for log-transformed mean electrical load $\log L_M$ for monitored households compared with synthetic households (July–December 2011). Within each dataset, non-coincident confidence intervals indicate significant between-months differences at the $\alpha = 0.05$ significance level; values marked with the same letters were **not** significantly different in the results of post hoc analyses ($p > .05$).

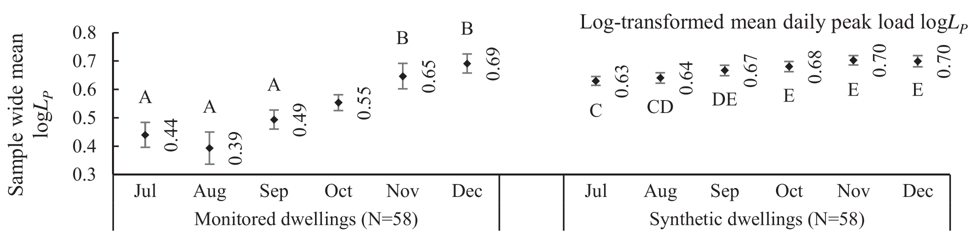

Fig. 7. 95% within-subjects confidence intervals for log-transformed mean daily peak load $\log L_P$ for monitored households compared with synthetic households (July–December 2011). Within each dataset, non-coincident confidence intervals indicate significant between-months differences at the $\alpha = 0.05$ significance level; values marked with the same letters were **not** significantly different in the results of post hoc analyses ($p > .05$).

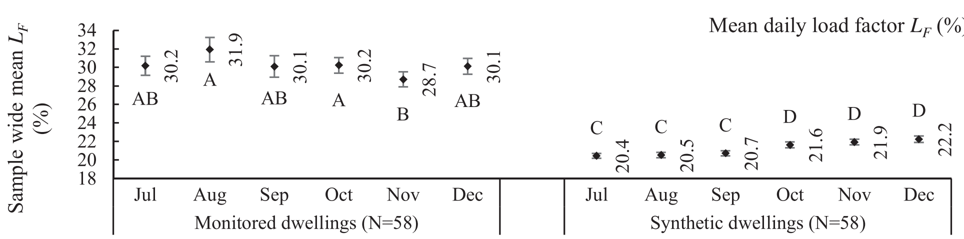

Fig. 8. 95% within-subjects confidence intervals for mean daily load factor L_F (%) for monitored households compared with synthetic households (July–December 2011). Within each dataset, non-coincident confidence intervals indicate significant between-months differences at the $\alpha = 0.05$ significance level; values marked with the same letters were **not** significantly different in the results of post hoc analyses ($p > .05$).

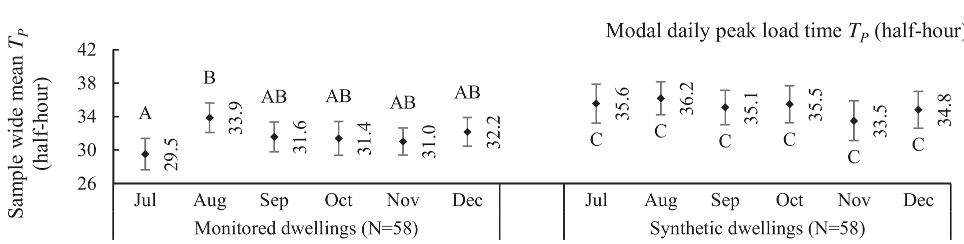

Fig. 9. 95% within-subjects confidence intervals for modal daily peak load time T_P (half-hour) for monitored households compared with synthetic households (July–December 2011). Within each dataset, non-coincident confidence intervals indicate significant between-months differences at the $\alpha = 0.05$ significance level; values marked with the same letters were **not** significantly different in the results of post hoc analyses ($p > .05$).

the log-transformed monitored metric exhibited significant month-on-month increases from September through December. In contrast, the log-transformed synthetic metric exhibited significant month-on-month increases from August through November.

3.2.2. Mean daily peak load L_P

For monitored mean daily peak load L_P, the results of the post hoc analyses (visualised in Fig. 7) revealed significant month-on-month increases in the log-transformed metric from September through November, but found no significant differences between July, August and September, nor between November and December. In contrast, the log-transformed synthetic metric exhibited no significant differences between consecutive months, but did exhibit a significant difference between July and September.

3.2.3. Mean daily load factor L_F

A clear difference can be seen in the confidence intervals for monitored and synthetic daily load factor L_F (Fig. 8): while mean monitored load factors only exhibited significant between-months differences when comparing November with August or October, mean synthetic load factors for July, August and September were all significantly lower than those for October, November and December.

3.2.4. Modal daily peak load time T_P

For peak load time T_P, the results of the post hoc analyses are visualised in Fig. 9. Among the monitored metrics, it was revealed that July peak load times were, on average, significantly earlier than August peak load times; otherwise no significant monthly differences were present. Among the synthetic metrics, however, no significant between-months differences emerged.

4. Discussion

4.1. Monthly variations in monitored electricity demand

The monitored data analysed for this paper were gathered from a small number of English households ($N = 58$, all dwelling in houses) between July and December 2011 as part of the Energy Follow-Up Survey (EFUS). This clearly precludes extrapolation from or generalisation of the results on a national scale, and the founding of any energy policy recommendations on the basis of the reported findings would be ill-advised. However, the results support previous observations of seasonal variability in overall electricity demand, while the findings that load factors, peak loads and peak load timing can vary significantly between months are considered novel. The conclusion that household load profile shapes can vary significantly between months has implications for future load profiling exercises, suggesting that treatment and validation of seasonal variability should account for more than just overall electricity demand; this assertion is further supported by the comparison of monitored and synthetic metrics, and is discussed further in Section 4.2.

Monitored daily load factors were, on average, significantly higher in August and October compared with November. Given that higher load factors represent less "peaky" daily load profiles, the higher likelihood of homes being vacated during August—the peak UK holiday season [30]—offers a possible explanation for these results, as an unoccupied dwelling would likely exhibit consistent base-level demand. To the authors' knowledge, no previous studies of seasonal variation in load factors are reported in the literature: the results presented in this paper suggest that further investigation is required to understand these effects.

Averaged across the EFUS58 sample, log-transformed mean daily peak load exhibited significant month-on-month increases from August through November. This finding was consistent with McLoughlin et al. [25], who attributed an upward trend in peak loads between July and December to seasonal variations in lighting demand and occupancy. Given the increasing proportion of UK electricity expected to be generated through wind and solar PV technologies [5]—both of which are prone to seasonal variability [8,29]—the findings that mean and peak loads can vary significantly between months are expected to have implications in the sizing and operation of electricity storage systems required for balancing supply and demand.

On average, monitored modal peak load times were significantly earlier in July compared with August. McLoughlin et al. [24] identified instant electric showers and plug-in electric heaters as significant predictors of earlier peak load times in Irish households; however, both were absent from the households studied here. A possible explanation may be that the August holiday season effected a reduction in early morning peak loads, as occupants rose later and spread morning activities over a longer time period. However, in the absence of detailed information regarding the behaviour of the EFUS58 householders, it is not possible to determine the veracity of such an explanation.

4.2. Representation of monthly variations in electricity demand predictions

It is important to note that the CREST model used to generate the synthetic data analysed in this paper was developed using nationally averaged data: occupancy modelling was based on 2011 UK TUS data, while the energy demands of appliances were derived from UK market statistics and adjusted to represent dwellings in the East Midlands of the UK [36]. Failure of the tool to accurately predict the electricity demand of the EFUS58 households is therefore not unexpected, as the EFUS58 sample was not representative of the UK domestic stock. Furthermore, synthetic households were only partially matched against their monitored counterparts: underestimation of mean electrical loads was likely due in part to the assumption that no more more than one of each appliance type was present in each dwelling, along with the CREST tool's upper limit of 5 occupants. Discrepancies in the monthly trends identified in the monitored and synthetic data do however indicate shortcomings in load profile modelling that fails to account for seasonal variation in occupant behaviour and appliance use.

Monthly trends in monitored mean electrical loads and peak loads were generally well represented in the CREST-generated synthetic load profiles (Figs. 1 and 2), although the scale of monthly variation of all four electricity demand metrics was underestimated. The underestimation of monthly variation in mean electrical load was consistent with CREST model validation findings reported by Richardson et al. [36]. Richardson et al. cited a lack of seasonality in the CREST occupancy model, and conceded that consideration of seasonally varying lighting demands alone was insufficient for predicting monthly differences in overall demand. The identification of underestimated monthly variability in peak loads, load factors and peak load times (Figs. 2–4) extends previous evaluation of seasonality in the CREST model, and strengthens the case for incorporating seasonal variation of occupancy and activity profiles in future modelling exercises.

The comparison of the ANOVA test results for monitored and synthetic load factors (Fig. 8) was particularly striking: while monitored load factors exhibited no clear monthly trend and few significant between-months differences, synthetic load factors demonstrated a clear upward trend between July and December 2011, with significantly higher synthetic load factors in the final three months of the year compared with July through September. It therefore appears that the CREST model overestimates of the influence of lighting demands on monthly variation in load factors. This does not necessarily mean that the predicted variability in lighting demands was inaccurate, as it is possible that the effects of lighting on monitored load factors were masked by other appliances whose influence was underestimated in the CREST model; however, the results offer evidence that lighting loads are not key drivers of monthly variation in load factors. Unfortunately, the availability of only household-level demand data in the EFUS dataset meant that the influence of individual appliances could not be analysed.

The only significant between-months difference in monitored peak load times, between July and August, was not predicted in the corresponding synthetic metric. The monitored difference was speculatively associated with the August UK holiday season (Section 4.1), and failure to reproduce the monitored July-vs-August difference in peak load times may again be a consequence of a lack of consideration of changes to occupancy and behaviour during vacation periods.

4.3. Limitations and recommendations

As noted in Section 4.1, the size and make-up of the EFUS58 sample means that the reported results cannot be generalised or extrapolated to a national level. Further to this, the influence of socio-demographic, dwelling and appliance characteristics were unaccounted for, meaning that identification of specific groups, outside of the EFUS58 sample, to which the results may apply is also difficult. While smart-metering is set to facilitate gathering of household electricity demand data on a national scale [14], it is recommended that collection of such data be paired with household surveys such that the influence of household characteristics on seasonally varying load profile shapes may be analysed. Long-term monitoring of electricity demand at the individual appliance level, as previously called for by Yilmaz et al. [39], is also recommended in order to facilitate investigation of how individual appliances contribute to seasonal variations in electricity demand. Documentation of the number and type of appliances found in dwellings is also necessary if synthetic dwellings are to be accurately defined in future bottom-up load profiling exercises.

In analysing monthly variability in the electricity demand metrics derived from the EFUS58 sample, it was assumed that householders and their lifestyles were unchanged throughout the monitoring period, and that all monthly variability was driven by seasonal effects. However, the metrics could at any point have been impacted by undocumented occupancy or lifestyle changes, such as changes in householder, employment status, or occupant health issues. The keeping of diaries documenting major changes in householders, lifestyles and appliance ownership throughout future monitoring is recommended, such that seasonally-driven variations in demand may be distinguished from variations precipitated by one-off events. The investigation of demand data gathered over periods of two or more years would also be valuable in identifying whether seasonal trends are consistent between years.

Specific influences of outdoor environmental conditions on electricity demand have not been investigated in this study. As none of the EFUS58 monitored dwellings reported the presence of electric space or water heating, outdoor temperature is not expected to have been a direct driver of monthly electricity demand variations; however, it may be reasonable to expect negative correlations between outdoor temperature and electricity demand for lighting and clothes drying. Cooler evening temperatures may also be expected to increase electricity demands associated with in-home activity as occupants spend less time outdoors. Analysis of electricity load profiles alongside weather data is recommended in order to identify relationships between the two, and to enable weather-driven effects to be separated from other occupancy- and activity-driven variations.

The absence of electrical space and water heating from the monitored dwellings in this study is a further barrier to generalisation of the results presented, as space and water heating accounted for 22% of UK domestic electricity consumption in 2017 [6]. The value of understanding the influence and variability of these demands will only increase as the UK sees further electrification of domestic heat [20]. Analysis of electricity demand data drawn from a sample incorporating electric heating, including low-carbon technologies expected to be implemented in the coming decades, is necessary to understand the extent to which monthly variability in heating demands will influence overall load profile shapes; in particular, whether the presence of electric heating will result in significant monthly differences in load factors and timing of peak loads.

The electricity demand metrics analysed in this paper were calculated from 30-min mean loads, whose use was motivated by the expected output of UK domestic smart meters. However, authors such as Good et al. [18] and Wright and Firth [38] have advocated using finer resolutions, the latter warning that logging at intervals longer than 2 min is insufficient for capturing the fine detail of household load profiles. In the context of the reported work, the use of 30-min mean loads will have caused an underestimation of true daily peak loads, and therefore an overestimation of load factors. The availability of loads monitored at 10-s intervals in the EFUS dataset presents an opportunity to investigate the discrepancies between peak loads and load factors calculated at various resolutions: such a study would provide insight into how peak loads and load factors derived from 30-min smart meter data should be interpreted.

The reported electricity demand metrics described load profiles at the individual household level; however, domestic electricity distribution networks are designed at the system level, with component sizing generally determined on the basis of expected maximum demand on the network as a whole [22,31]. Although per-household electricity demand metrics may be useful for design decisions at household level, such as sizing of in-home batteries or valuation of electricity generated by PV arrays, they are less meaningful in the context of network design. In light of the significant monthly variability observed in per-household metrics, similar investigation of community-level metrics describing time-coincident demand is recommended in order to determine the nature of seasonal variability at community level.

Failure of the reported load profiling exercise to accurately reproduce between-months differences in load factors and peak load times may reflect shortcomings in the operation of the CREST model rather than the model's architecture. As noted in Section 4.1, occupancy and behaviour in UK households may change dramatically in August due to the peak holiday season, but no allowances were made for holidays when generating synthetic data: a simple approach to modelling households vacated during holidays would be to switch their occupancy to zero when generating load data for the relevant days, while non-work days in occupied households could have been approximated as weekend days. McQueen et al. [26] previously observed that "atypical situations such as holiday periods must be considered explicitly" when forecasting load profiles at network level: the reported results further support this recommendation.

5. Conclusions

Through analysis of half-hourly electricity demand data from a sample of 58 English households, this paper shows that seasonal variation can have significant effects on multiple aspects of electricity demand in English homes. Using ANOVA tests, significant monthly variability was identified not only in mean electrical demand, but also in daily load factors and the scale and timing of daily peak loads.

A set of synthetic load profiles, generated using a time-of-use-based load profiling tool, were found to exhibit monthly variations in load factors and timing of daily peak loads inconsistent with monthly variations in the monitored load profiles. Monthly trends in monitored mean and peak loads were generally reflected in the synthetic data; however, the scale of between-months differences tended to be underestimated, particularly so for peak loads. These discrepancies demonstrate that failure to account for monthly variability in occupant behaviour can result in failure to accurately reproduce such variability in simulated load profiles.

The presented results demonstrate that validation of monthly trends founded solely on overall electricity demand risks false affirmation of a model's ability to accurately represent seasonal variation in daily load profile shapes. It is concluded that any rigorous validation of seasonality in load profiling must consider multiple characteristics of load profile shapes. The metrics describing load factors, peak loads and peak load times presented in this paper offer a starting point, but further analysis of monitored household electrical load profiles is recommended to identify and quantify additional seasonally varying aspects of domestic electricity demand. Analysis of high-resolution data monitored at the appliance level is also recommended in order to investigate the contributions made by individual appliances to seasonal variations in household electricity demand, while investigation of longer and richer monitored datasets including weather conditions is required to separate the influence of changing environmental conditions from occupancy- and activity-driven effects. Finally, it is necessary to gather such data from a nationally representative sample in order to determine whether and how the reported results can be generalised.

Funding

This research was made possible by Engineering and Physical Sciences Research Council (EPSRC) support for the London-Loughborough Centre for Doctoral Research in Energy Demand [grant number EP/L01517X/1].

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