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The nature of domestic electricity-loads and effects of time averaging on statistics and on-site generation calculations

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Abstract

This paper describes exploratory analyses of domestic electricity-profiles recorded at a high time resolution of 1 min on eight houses. It includes a detailed analysis of the effects of time averaging. For dwellings with on-site generation, such as micro-CHP, a better understanding of electricity profiles is important for the economic analysis of systems, and to examine the effects of widespread on-site generation on local electricity-networks. Most load data are available at half-hour intervals; averaging data over periods longer than a minute is shown to under-estimate the proportions of both export and import. The frequency distribution of loads is shown to be highly skewed, with varying distributions and an average load factor of 0.1. Further study is needed to develop more general relationships for a large sample of houses, to apply in design and research.

Keywords: Domestic; Energy; Electrical; Load; Generation

1. Introduction

Most published information on electrical loads is for a time resolution of half an hour, which is the standard interval for load analysis and electricity trading in UK industry [1],

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although shorter intervals, e.g. 15 min, are used in some countries. A half-hour resolution is sufficient to show variations in load aggregated across many customers (for example, at a transformer), and is entirely appropriate for domestic profiles used for billing [2]. However, this resolution hides high-frequency variations in loads over timescales of the order of a minute in individual buildings. In dwellings particularly, loads can vary greatly over a few minutes due to the small number of appliances and patterns of usage. On-site generation is becoming more widespread for dwellings (for example, photovoltaic panels, micro-CHP and micro-wind) and is considered by the UK government to have great potential to increase [3] due to improving technology, falling costs relative to fuel prices, and environmental concerns. This makes it more important to understand the nature of domestic loads. Since the value of exported energy is at present much less than the value of energy used on site, the economics of the scheme (rather than the carbon savings) depend largely on the proportion of the power generated which is used on site. This work describes an analysis of data collected at 1 min intervals over long periods from seven homes in the north-west of England. Data from two houses are analysed in detail over short periods and over one winter week; the analysis is exploratory in nature, but does highlight key behaviour and areas of importance for a more general analysis across a larger dataset.

Following the background and description of the data-sets, the general nature of domestic loads is discussed, and the effects of time averaging are described. Then, for hypothetical on-site generation at various output levels, the effects of time averaging on the proportion of power imported, and the proportion of generation exported, are analysed. Mathematical relationships between these quantities are defined. Frequency distributions of loads are then considered, and shown not to follow any standard statistical distributions. Finally, conclusions are drawn and recommendations made for further study.

2. Background

There is a considerable literature on short-term load forecasting for the control of the whole electricity system, typically only a few hours ahead, but the techniques used here are not normally applicable to analysis of load patterns for buildings. In the UK, average profiles for different customer types are produced and used in settlement (i.e. the process of allocating energy use to consumers at different times of day and billing suppliers), on a half-hourly basis [2]. The data-sets and the literature on UK domestic-loads are quite limited.

Mansouri et al. [4] carried out a detailed survey of appliance ownership and usage in UK households and inferred from this energy usage. Lane [5] used Generalised Linear Model statistics to predict half-hourly load-patterns of different household/house types, based on a sample of half-hourly data from around 650 houses in the north west of England. Stokes [6] developed a model of domestic lighting-demand, and models of other electrical appliances [7] in relation to low-voltage network performance analysis. Newborough [8] refers to 1 min electrical load data collected from 30 houses, but most of his analysis is for one house, for which basis statistics and an example one day profile are given. Abu-Sharkh [9] in a paper on micro-grids gives high resolution data (logging interval not stated) for one house and proposes a simple model to generate load patterns for a set of hypothetical households and dwellings. Yao and Steemers [10] describe in more detail a stochastic model to generate electrical-load profiles for hypothetical households and dwellings. Stokes et al. [11] analysed the effects of diversity (numbers of houses) on the collective maximum-demand using a detailed stochastic consumption model, itself based on appliance field-data. Firth [12] analysed 5 min data from domestic photovoltaic installations on 109 homes over 2 years. His analysis was restricted to the generation rather than house demand, but the latter could be calculated from the data-set which is one of the largest of its kind.

Domestic load-data are usually collected at intervals of 1, 5, 10, 15 or 30 min. There appears to be no detailed analysis of the statistical nature of domestic loads at high time-resolution from field data, or of the effects of time averaging. The authors are unaware of any substantial data-sets at high resolution in the public domain.

When analysing on-site generation systems, the use of half-hourly data will often overestimate the proportion of generated energy used on site, and hence under-estimate both the export and import. This usually happens when large, short-duration load 'spikes' occur which are smoothed out by the averaging. Electrical energy 'spilled' onto the network, i.e. exported, is still used elsewhere and not 'wasted'. But current financial arrangements in the UK mean that the commercial value of an exported unit is much lower than that of a unit used on site, and even may be zero if there is no mechanism for recovering its true value. There is therefore considerable value in having accurate information about the proportion of generated power used on site. Such information can come either directly from field data with limited applicability, or more generally from models produced from a statistical analysis of load data from many households. Furthermore, if several houses are connected to a common upstream local-generator such as a wind turbine or community CHP system, it is necessary to know the effects of diversity, i.e. the combined domestic load, in order to calculate exports.

3. Data-sets

Data-sets of 1-min load (kW), volts × amps/1000 (kVA), and voltage, were available from eight homes in the north west of England between December 2004 and September 2005, with varying amounts of missing data. The national grid frequency (Hz) was also logged at one house. These houses were not chosen as a statistical sample, but were simply the homes of employees of one company willing to allow measurements to take place. Most of the analysis was carried out on the data from two homes, one with a relatively high-demand and the other with a low demand. There were several gaps in the data and a few errors, such as kVA values occasionally exceeding kW values, but data quality was generally high. A short interruption every few weeks was unavoidable at the point of data download from the datalogger to the laptop computer. Only complete or almost complete data-sets were used in the analysis.

4. Nature of domestic load

The average domestic electricity-consumption per Meter Point Administration Number (MPAN) in the UK for 2004 was 4068 kWh [13], including a proportion of consumers with electric space and/or water heating. This corresponds to an *average* load over the year of about 0.46 kW. Modern homes have a 100 A fuse, which allows a peak load of up to 23 kW (100 A × 230 V). However, peak loads are typically less than half of this.

Electrical loads for buildings, and domestic loads in particular, are the product of a complex interaction between patterns of appliance use, and the load signatures of the devices themselves (where 'device' here means any piece of mains electrical equipment). Some devices are 'always switched on', with constant load (e.g. set top box), or cyclic load (e.g. refrigeration). For other devices, usage is dictated by many factors including:

- weather conditions, e.g. use of tumble dryers; whether people are in or out;
- occupancy and occupant behaviour; cooking, use of lighting, entertainment, etc.;
- solar geometry, interacting with weather, determining daylight availability.

Occupancy periods and behaviour vary widely between households; some have very regular habits while others are much more chaotic. Even the cyclic refrigeration load will vary with room temperature and the frequency of door opening and restocking. Domestic profiles, without significant electric space or water heating-loads, can be interpreted visually in terms of:

- a 24-h base load of electronic devices permanently-on plus cyclic refrigeration loads;
- a varying load of the order of 100 s for lighting, TV, computers, etc., which reflect occupancy activities and daylight, varying fairly smoothly;
- Large load 'spikes' of short duration from a few 100 W up to a few kilowatts, due to high-power devices usually producing heat for large kitchen appliances, kettles, showers, etc.

In addition, there are various motor loads in washing appliances, central-heating systems, vacuum cleaners, lawn mowers, etc., on either fixed cycles or on–off control by occupants, but these are not usually large enough to be easily identified.

Consumption is typically higher in the winter due to electric heating, more lighting, lower cold-water feed temperatures, more use of tumble dryers, possibly more cooking, and some occupancy factors, such as more time spent indoors in the winter.

Fig. 1 shows the average 24 h load-profile for seven of the houses plotted half-hourly from between December 2004 and August 2005 (exact periods monitored varied between

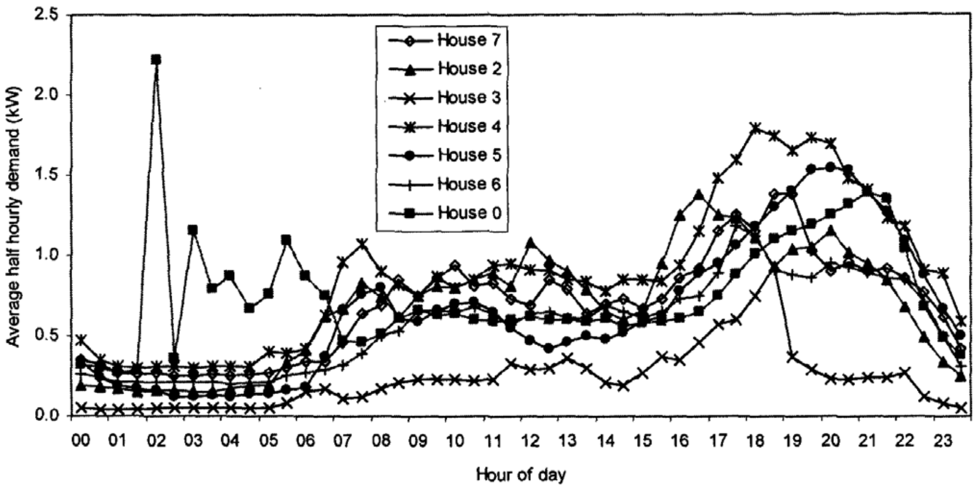

Fig. 1. Half-hourly average loads for eight different houses, averaged over approximately a year.

these months, and there were significant gaps in some cases). The atypical curve with a large load in the early morning is due to an off-peak hot-water heater. Apart from this, the load curves follow a similar pattern, but there are large differences in base load, overall consumption, time of evening peak and daytime use. One house shows a much lower consumption overall, and in almost every half hour, than all the other houses.

4.1. Effect of time averaging

Loads were logged as integrated values over a given time period, rather than instantaneous power values. Therefore, arithmetically averaging loads collected at one period over longer periods is precisely equivalent to actual logging over such longer periods. For example averaging power, or aggregating energy, from 1-min data over 5-min intervals gives the same numbers (ignoring logging errors) as logging at 5-min intervals. Note that other electrical quantities, such as voltage and current, may be measured as instantaneous values.

Two houses were selected for detailed investigation; House 3 which had the lowest demand of the eight, and House 7 which had a fairly typical high-demand, with a particularly high base-load. A typical domestic profile over one day, for House 7 is shown in Fig. 2 at a 1-min resolution and with the corresponding half-hour averages. This shows how half-hourly average loads are much lower and smoother than 1 min loads. Large but brief load spikes, for example the two around 16.00–17.00 (very probably use of a kettle), hardly affect the half-hourly average. This load pattern is very different from that for a large building, where there are much larger near-constant loads (for lighting, fans, pumps, computers, etc.) and the fluctuations minute-by-minute are quite small most of the time compared with the total load.

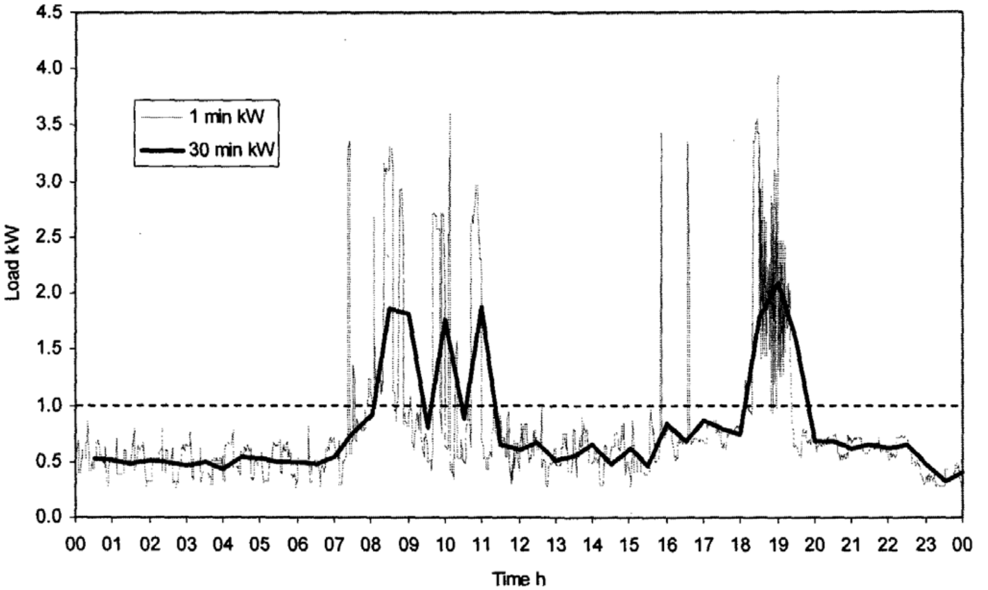

Fig. 2. Load profiles at 1 min and 30 min time resolutions for a single December weekday, for house 7. Dashed line shows 1 kW demand level, which is the average diversified peak-load for many houses.

Plotting 5-min data with 1-min data shows a superficially similar pattern over a day, i.e. the loads still appear spiky, but the longer averaging fails to capture the highest loads. The differences are much more obvious over a short period. Fig. 3 is a comparison of 1-min, 5-min and 30-min averaging, where the 5- and 30-min values are the average of the 1-min values at the end of the interval. (This was done in a Microsoft Excel spreadsheet by setting up dummy variables based on data and time for interval number, then using pivot tables to find the average over each time-interval.)

Although the 1- and 5-min curves follow closely at times of low and smoothly varying load, from about 18.00 to 18.30 and after about 19.20, in between these times the 5-min averaging fails to capture the rapid variations in load shown in the 1-min data – in fact the oscillations here have a period of 1 min. Comparison of 1 min and 1/2 min data by EA Technology Ltd., Chester, UK (reference not available) showed only small differences, i.e. loads do not normally change on a timescale of much less than about 1 min.

The pattern in Fig. 3 is probably due to electric cooking; an initial heating-up period at about 3.5 kW total followed by thermostatic cycling for about 50 min. Note that, if there had been 2 kW of on-site generation in this house (indicated by the horizontal line), the 30-min data would have suggested nearly all the loads would have been met from this after 18.30, while the l- and 5-min data show there would actually have been a significant import over this period – compare the areas under the three curves above the 2 kW line. In fact, the calculated imports for 2 kW generation over the two hours are 0.51 kWh if using 1-min data (close to reality), 0.32 kWh if using 5-min data and 0.05 kWh if using 30-min data.

Investigations were carried out into the statistical effects of time averaging. One-minute source data were used; this was averaged by software to mimic the effects of metering at longer intervals. The effects on various statistical parameters of averaging at 1, 5, 15 and 30 min, over 1 week in December for two houses, is shown in Table 1 for 24 h usage. Fig. 4 shows some of the statistics on a frequency plot, for 5 min averaging.

House 7 (discussed previously) had an mean load 2.8 times that of the lower use House 3 – the mean is of course unaffected by averaging period.

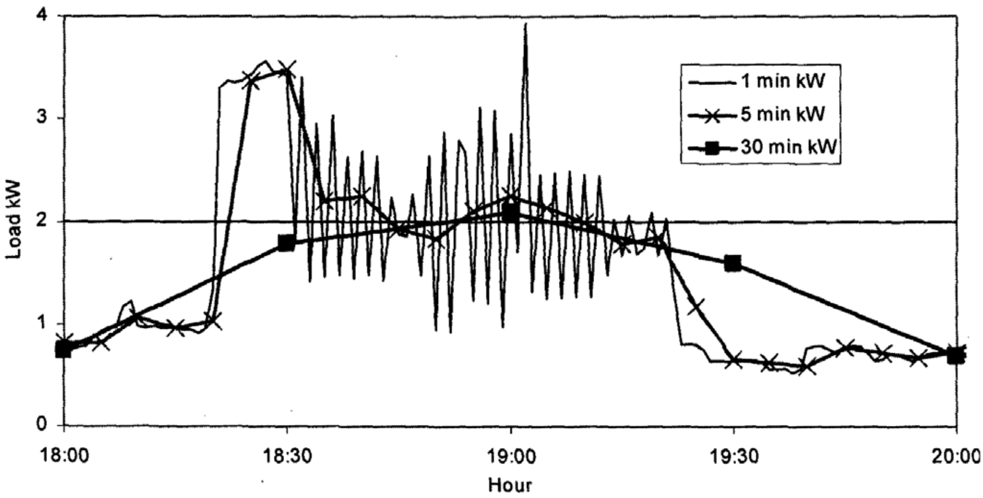

Fig. 3. Comparison of 1, 5 and 30 min averaging at time of intensive loads, for house 7.

Table 1
Effect of time averaging on various statistics, continuous for 1 week in December, for two houses

Statistics (kW)	House 3 with lower loads				House 7 with higher loads			
	1 min (%)	5 min	15 min	30 min	1 min (%)	5 min	15 min	30 min
Mean	0.308	0.308	0.308	0.308	0.856	0.856	0.856	0.856
Standard deviation	0.643	0.586	0.530	0.454	0.828	0.750	0.662	0.600
10th percentile	0.000	0.000	0.000	0.029	0.250	0.249	0.257	0.269
50th perc'. (median)	0.150	0.154	0.165	0.176	0.630	0.642	0.660	0.692
90th percentile	0.460	0.518	0.633	0.615	1.940	1.902	1.849	1.828
99th percentile	3.402	3.084	2.783	2.243	3.690	3.450	2.950	2.749
Maximum	8.830	6.455	4.219	3.081	8.920	8.822	4.929	3.058

The standard deviations for the two houses are fairly similar, and decrease significantly, as one would expect, as the averaging period is reduced. The 10th percentile is zero for house 3, because loads fell to zero frequently during the night – presumably there were no significant continuous loads such as standby. Averaging has a complicated effect on percentiles, increasing some and decreasing others, due to the distribution of loads. In both cases, the median (50 percentile) values were lower than the mean value, due to the highly-skewed load-distribution; time averaging increases this.

Sparse load 'spikes' mean that averaging reduces the 99 percentile significantly, but the 90 percentile value is increased in house 3 but decreased slightly in house 7, due to different load-patterns. Absolute maximum load values (at the 1-min level) are very similar at 8.8 kW between the two houses. Time averaging (except for 5 min) reduces these in a similar pattern in both houses to about 3.1 kW (35% of the 1 min peak) for 30 min – this is still about three times the peak level averaged across many homes.

A similar analysis was carried out over the same December week for typical 'occupied' periods when occupants are awake and active, and so usage is considerably higher. This was fixed as 07:00–09:00 and 16:00–21:00. It also roughly coincides with typical central-heating

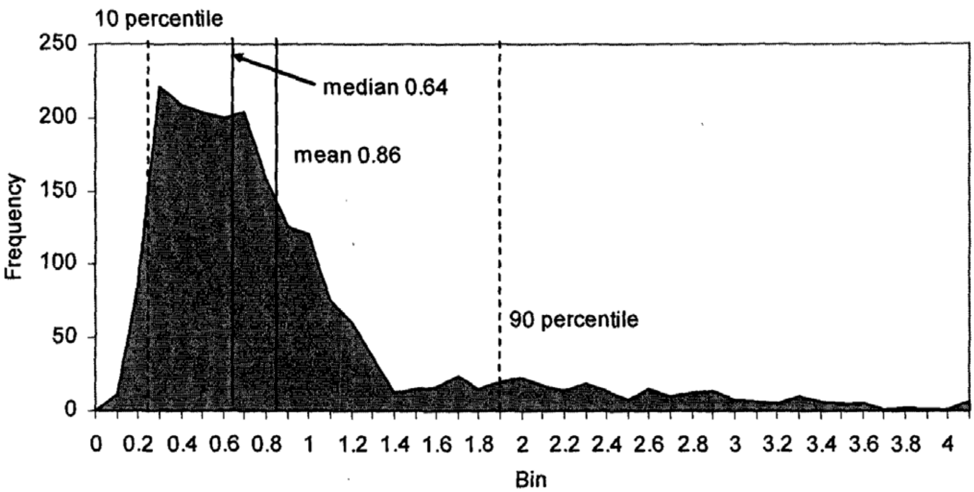

Fig. 4. Frequency plot for House B, 5 min averaging.

periods and hence possible run-times for micro-CHP systems. Results are given in Table 2. Overall values are of course higher, but the effects of time averaging are similar.

A key question for research into on-site generation is the effect of time averaging interval on predictions of on-site use, as well as the import and export for different power levels. Knowing these can help to determine the usefulness of say half-hourly data or the need for high-frequency measurement. For a given period, let I be total imports, D total demand, and G total on-site generation. Electricity generated and used on site is then $D - I$.

The proportion of electricity imported P_i is then

$$P_i = \frac{I}{D} \tag{1}$$

Similarly, the proportion exported P_e is

$$P_e = \frac{G - (D - I)}{G} \tag{2}$$

where G is the generation, which at a given time is total demand minus imports. It then also follows that, if $G = D$, i.e. total generation equals total demand over the period, then Eq. (2) reduces to Eq. (1) so we have $P_t = P_e$. Furthermore, since $I = D - G(I - P_e)$, from Eq. (1) P_e and P_i, are related by

$$P_i = 1 - \frac{G}{D}(1 - P_e)$$

As these equations only involve totals, they hold true whatever the actual patterns of usage and generation. Also, if $G > D$, say $G/D = 1 + \delta$ where $\delta > 0$, then

$$P_i = 1 - (1 + \delta)(1 - P_e) = P_e - (1 - P_e)\delta < P_e$$

since $(1 - P_e)\delta$ must be positive. A similar inequality follows the opposite way. To summarise then,

$$\begin{aligned} G = D &:\Rightarrow P_e = P_i \\ G > D &:\Rightarrow P_e > P_i \\ G < D &:\Rightarrow P_e < P_i \end{aligned}$$

To give some qualitative insight, values of P_i were calculated for different averaging periods from one week of data (the same period and houses as used in the preceding statistical analysis). It may be assumed to a high degree of accuracy that the 1-min results represent the 'true' demand, import and export values.

Table 2
Effect of time averaging on various statistics during occupied periods in 1 week during December, for two houses

Statistics (kW)	House 3 with lower loads				House 7 with higher loads			
	1 min (%)	5 min	15 min	30 min	1 min (%)	5 min	15 min	30 min
Mean	0.515	0.515	0.515	0.515	1.253	1.253	1.253	1.253
Standard deviation	0.835	0.754	0.659	0.566	1.035	0.911	0.750	0.644
10th percentile	0.120	0.124	0.126	0.151	0.520	0.546	0.615	0.666
50th perc'. (median)	0.270	0.280	0.302	0.352	0.930	0.959	0.983	1.000
90th percentile	1.031	1.310	1.244	1.155	2.850	2.453	2.420	2.221
99th percentile	4.441	3.732	3.532	2.999	4.492	3.907	3.239	2.923
Maximum	8.830	6.930	4.175	3.075	8.920	8.822	4.929	3.058

The proportion of power imported for constant generation is shown for the two houses in Table 3 (note these homes did not have generation installed: the results are hypothetical). Although constant generation is unlikely with present technologies, it provides the simplest case for analysis of export and import, and a comparison against generation during occupied periods. Proportions drop as the generation level rises, as one would expect, since, for more of the time, the generation exceeds the level of house demand.

For the higher-load house 7, the averaging period makes surprisingly little difference to the proportion of electricity imported, except for the 2 kW generation where the values are low but differences are large (because the load exceeds 2 kW for only short periods of time, for which the averaging process has a large effect). For a 1 kW generator, 30-min averaging under-predicts the import proportion by around (26–21%)/26%, i.e. 19%.

For house 3, the effects of time averaging are larger because of the smaller demand. For a 1 kW generator, 30-min averaging under-predicts the import proportion by around 47% (16% instead of 30%). Although it might be expected that the figures for the two houses would be similar if the generation level was set equal to the average demand, this is not the case, due presumably to different load-patterns. In house 3, generation at average demand produces 49% imports compared to 30% imports for house 7, at the accurate 1-min level; these drop slightly with averaging period.

A similar analysis was carried out, with generation restricted to the occupied periods as defined previously. Results are given in Table 4. Again this shows time averaging has little effect at low levels of generation, when a high proportion is used on site, but much larger effects at higher, more realistic, levels. At 1 kW, the calculated import proportion drops by 40% (house 3) and 12% (house 7), respectively, from 1 min to 30 min averaging. Generating at average load for the occupied periods again gives very different results between the houses.

Also relevant is the proportion of generated power which is exported, which does not bear a simple relation to the proportion of energy imported. As shown in Table 5, the export proportion reduces, but only marginally, for longer averaging periods across all levels of generation. In contrast to the imported proportion, the differences are small for the 2 kW generation, when most is exported. Overall, the 5-min data produce very similar numbers here to the 1-min data. Typical differences in proportion of export calculated

Table 3
Proportion of energy imported for different levels of hypothetical continuous generation over one week in December

Generation level, 24 h (kW)	House 3: proportion imported for different averaging periods				House 7: proportion imported for different averaging periods			
	1 min (%)	5 min (%)	15 min (%)	30 min (%)	1 min (%)	5 min (%)	15 min (%)	30 min (%)
0.25	53	53	51	49	72	71	71	71
0.50	41	39	35	30	49	49	49	48
0.75	35	32	27	22	35	34	33	32
1.00	30	26	21	16	26	25	23	21
2.00	13	10	7	3	11	8	5	3
$A = 0.308$[a]; $B = 0.856$[a]	49	48	46	43	30	30	28	27

[a] Generation equal to average demand for each house.

Table 4
Proportion of energy imported, analysed for generation and consumption during occupied periods only, for different levels of hypothetical generation, over 1 week in December

Generation level, occupied hrs (kW)	House 3: proportion imported for different averaging periods				House 7: proportion imported for different averaging periods			
	1 min (%)	5 min (%)	15 min (%)	30 min (%)	1 min (%)	5 min (%)	15 min (%)	30 min (%)
0.25	59	59	58	57	80	80	80	80
0.50	44	42	39	36	61	61	61	61
0.75	37	35	30	26	45	44	43	43
1.00	32	28	24	19	34	33	31	30
2.00	15	12	8	5	16	12	8	5
$A = 0.515$[a]; $B = 1.253$[a]	43	42	39	35	27	25	23	21

[a] Generation equal to average demand for each house.

using 1-min and 30-min averaging are of the order of 10%; higher resolution always giving higher exports. There are very wide differences between the houses due to different levels of demand.

A similar exercise for demand and generation during occupied periods only gave the results shown in Table 6. This shows very large differences between the houses due to the different levels of demand; for example, at 1 kW generation, about two-thirds of power is exported from house 3 but only one-sixth from house 7.

It is interesting to note that the effects of time averaging are generally less on the export proportion than on the import proportion. An explanation of this is suggested by considering Fig. 2. At 1 kW generation, import proportion is the area under the load curve above the dashed 1 kW line. Export proportion is the area between the dashed line and the load curve when the latter is below the dashed line. Visual inspection suggests that import proportion will be affected more than export proportion when the averaging period is increased. Essentially, this is because the sharp peaks above 1 kW are reduced more dramatically by averaging than the shape of the smoother load-curve below 1 kW.

While it is not possible to draw any general conclusions about the effect of time averaging on the import proportion, a consideration of values in Tables 5 and 6 suggests that

Table 5
Proportion of generation exported for different levels of continuous generation, calculated using different averaging-periods, over one December week

Generation level, 24 hr (kW)	House 3: proportion generation exported, by averaging periods				House 7: proportion generation exported, by averaging periods			
	1 min (%)	5 min (%)	15 min (%)	30 min (%)	1 min (%)	5 min (%)	15 min (%)	30 min (%)
0.25	43	41	39	37	2.7	2.3	1.8	1.3
0.50	64	62	60	57	13	13	12	11
0.75	73	72	70	68	26	25	23	22
1.00	78	77	76	74	37	36	34	33
2.00	87	86	86	85	62	61	60	59
A = 0.308[a]; B = 0.856[a]	49	48	46	43	30	30	28	27

[a] Generation equal to average demand for each house.

Table 6
Proportion of generation exported during occupied periods only, for different levels of generation, calculated using different averaging periods, over one December week

Generation level, occupied hrs (kW)	House 3: proportion generation exported, by averaging periods				House 7: proportion generation exported, by averaging periods			
	1 min (%)	5 min (%)	15 min (%)	30 min (%)	1 min (%)	5 min (%)	15 min (%)	30 min (%)
0.25	16	15	13	11	0	0	0	0
0.50	42	40	37	34	2	2	2	1
0.75	57	55	52	49	8	7	6	4
1.00	65	63	61	58	17	16	14	12
2.00	78	77	76	75	47	45	43	41
$A = 0.515$[a]; $B = 1.253$[a]	43	42	39	35	27	25	23	21

[a] Generation equal to average demand for each house.

for exports above 10%, adding between 3 and 8 percentage points to the value calculated with half-hour averaging, will give an estimate for the 1-min (~actual) export percentages for these houses. The fact that the houses considered have widely differing load-patterns suggests that this is more generally applicable, but analysis of more load-profiles would be needed to confirm this.

The reader may note that the last lines in Tables 3 and 5 are the same, as also are the last lines in Tables 4 and 6. This is no coincidence, but follows from the relationships given earlier.

4.2. Distributions of loads

Fig. 5 shows histograms of the house demands, over one week, at the 1-min time interval level during 'occupied' periods; this is truncated at 5 kW since the frequency of higher

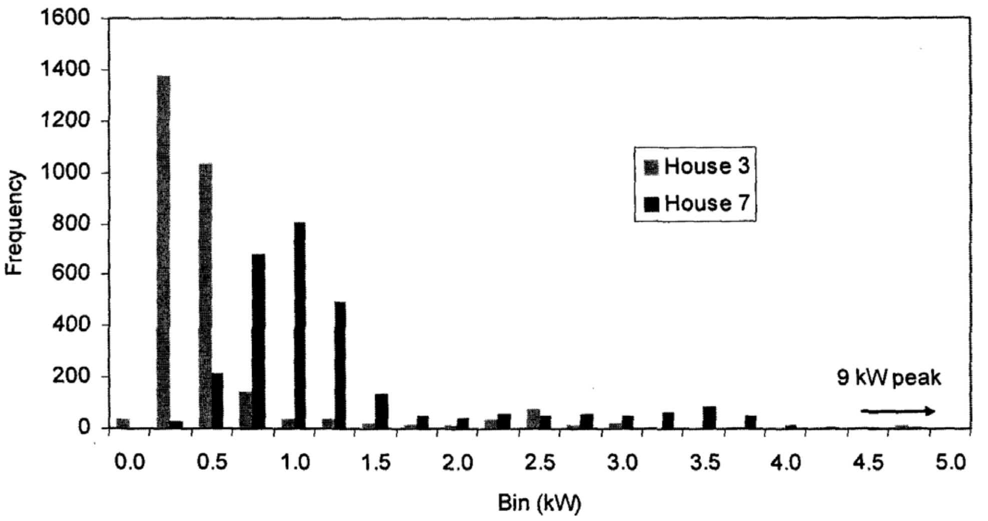

Fig. 5. Histograms of 1 min loads for houses 3 and 7, truncated at 5 kW.

loads is too small to see on the chart. Both distributions are highly skewed to the right: house 3, with lower loads, is skewed the most. If one draws a vertical line at a given bin level, say 1 kW, then all loads in the distributions to the left of the line can be fully met by generation at this level, while all loads to the right will require some import.

Plotting frequencies with a $\log_{10}$ scale gives more information about the low frequencies, particularly for higher loads, as shown in Fig. 6 (the y-axis numbers are still frequencies but the scale is $\log_{10}$). Note that zero frequencies cannot be represented on this scale but are effectively zero height columns. Isolated clusters of high loads, seen here at around 7 and 9 kW bins for house 3 and house 7 respectively, are typical of individual house loads, probably representing particular appliances with large heating-elements. Neither type of distribution appears to fit any of the analytical distributions of statistics, although for the normal scale, there is a reasonable fit to a gamma or beta distribution if high loads are excluded (this is analogous to the findings of Herman and Gaunt [14] investigating voltage drops on low-voltage networks).

Data were available for seven of the eight houses for the week 1–7 March 2005. A small number of erroneous negative values were found in the data at times of low load; these were replaced with averages of the adjacent values, which were often the same. Frequency curves for the 1-min data are given for these in Fig. 7 (strictly speaking these are discrete data, but curves are plotted instead of bars for clarity of comparison). The aggregate curve is the summed frequencies divided by 7, i.e. the average frequency in each bin. Values start at 0.25 kW on the x-axis representing frequency of loads below 0.25 kW. Two distinct shapes are evident; four houses with the highest frequency in the first bin (<0.25 kW) and three houses with the highest frequency in the 0.25–0.5 kW bin. Secondary peaks at higher bins are also evident for some houses. The highly-skewed nature of the distributions is emphasised by the overall mean-load line at 0.8 kW: all peak frequencies lie to the left of this. Clearly, the frequency curves vary widely in shape but are consistently highly skewed to the right.

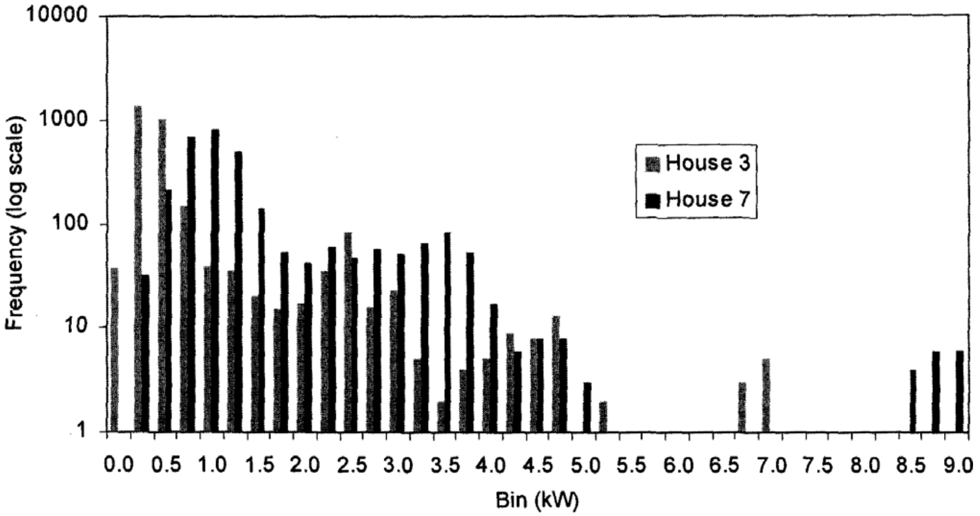

Fig. 6. Histograms of 1 min loads for houses 3 and 7, plotted with a $\log_{10}$ scale for full range of loads (note zero frequencies cannot be represented on a log scale, but are absent columns).

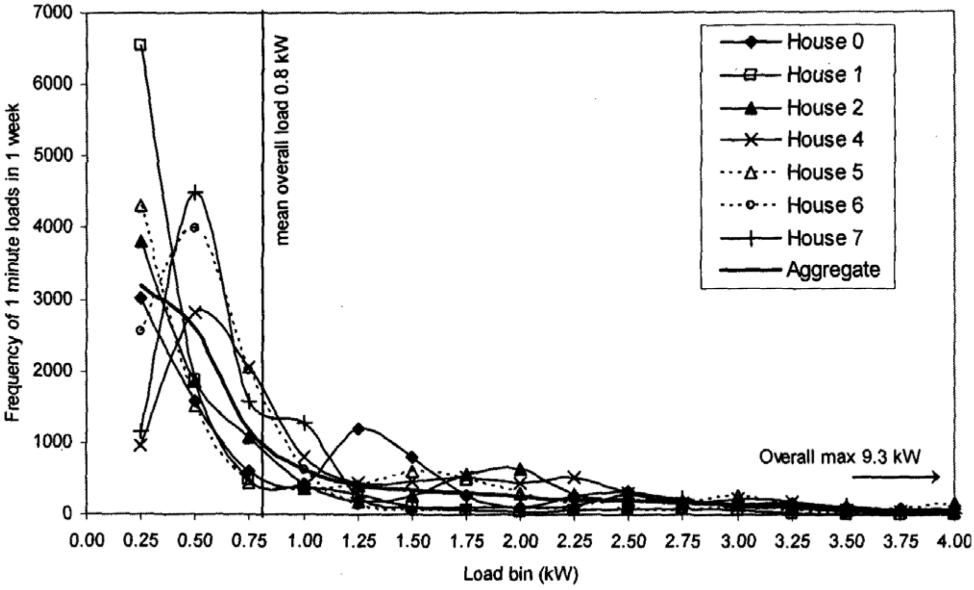

Fig. 7. Frequency curves of 1 min loads for seven houses, 1–7 March 2005, truncated at 4 kW.

Table 7
Descriptive statistics for 1 min loads for seven houses, 1–7 March 2005

	House							
	0	1	2	4	5	6	7	Overall calculation
Maximum	7.96	6.06	8.50	9.32	8.56	7.12	8.63	9.32 Maximum
Minimum	0.00	0.00	0.08	0.16	0.00	0.08	0.14	0.00 Minimum
Mean	1.20	0.36	0.88	1.04	1.01	0.58	0.76	0.83 Mean
St deviation	1.34	0.52	1.02	0.93	1.31	0.69	0.82	0.95 Mean SD
Load factor	0.15	0.06	0.10	0.11	0.12	0.08	0.09	0.10 Mean load factor

Corresponding descriptive statistics are given in Table 7. While this is in no sense a representative sample, it does include a wide variety of usage patterns and highlights some similarities and differences which may apply more generally. There is less variation in peak load (highest: lowest ratio = 1.54) than in the mean load (ratio 3.33).

Hence, load factors (ratio of mean load to peak load) vary widely, mainly due to the variation in mean load, averaging about 10%. Standard deviations also vary widely, but are in all cases quite similar to the mean-load value: this shows that the variability of load size, about the mean, increases roughly linearly, for these houses, with average load.

These results illustrate the problem of sizing on-site generation for a high level of on-site use; usage varies widely between households, and the very low load-factors mean that larger loads will inevitably require grid import, until effective storage technologies are developed.

5. Conclusions

There have been few published studies of high resolution domestic electrical-data. This paper has analysed data gathered at 1-min intervals for seven houses, two in detail, and considered the effects of time averaging, and import and export proportions for on-site generation.

The effects on load analysis of increasing the logging interval from 1 to 5, 15 and 30 min (accurately modelled here by numerical averaging) have been investigated. Visual inspection of load curves plotted for different intervals clearly shows how sharp peaks are reduced or disappear as the averaging period is increased, and high-frequency cyclic loads (typically for heating appliances) are only evident for short logging-periods of around 1 min. This confirms others' findings that logging at 1 or 2 min intervals is necessary to capture the fine detail of load patters. Averaging over longer periods has a significant effect on basic statistics (except the mean), in particular reducing maximum and high percentile values, but increasing the median.

Monitored demand data, at various logging intervals including half-hourly, is often used to calculate the likely performance of on-site generation systems under development. Usually, it is assumed that the data are sufficiently accurate for this purpose. Hypothetical on-site generation was modelled alongside the real loads to investigate the effects of logging interval, using time averaging. This was done for generation at various output levels, operating either continuously or during occupancy only, for a winter week in two sample-houses with widely different load-patterns.

The proportions of demand which would have to be imported because it exceeded generation, and the proportions of generated power exported because it exceeded house demand, have been calculated. It has been shown, for these scenarios, that time averaging has small effects on export proportions for mid-range generation levels (of the order of average house-demand), but a larger effect on import proportion. Effects vary between houses. For import proportion, the patterns are more complicated. Mathematical relationships between the import and export proportions have been derived. It is shown that if total generation over a period equals total demand, regardless of profiles, then the export and import proportions will be equal. If total generation exceeds total demand, then the export proportion will exceed the import proportion, and *vice versa*.

For evaluation of on-site generation, a logging period of 5 min seems a reasonable compromise to give good accuracy with reasonable data volume. Even half-hourly profiles, from individual homes, can give reasonable estimates of export proportion in some cases, but is not reliable for import proportion. However, using standard domestic profiles averaged from many homes is a completely different calculation and is not applicable to a single house, due to the effects of diversity (Stokes et al., 2006). Diversified profiles are only applicable to community generation with a single point of import and export upstream of a large number of houses and the generator – but standard profiles are unlikely to apply to a particular community.

It is shown that frequency distributions of 1-min loads for seven houses are all very skewed to the right but with different shapes. Mean and standard deviations vary widely between houses, but are similar to each other for a given house. Load factors average around 0.1. Further study is needed to improve understanding of the frequency distributions of loads for the evaluation of distributed and on-site generation. Analysis could be extended to a larger number of houses to improve the generality of the results.

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