Electrical-end-use data from 23 houses sampled each minute for simulating micro-generation systems

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Abstract

An improved understanding of the consumption patterns, end-uses, and temporal variations of electrical loads in houses is warranted because a significant fraction of a society's total electricity consumption occurs within residential buildings. In general, there is a lack of high-temporal-resolution data describing occupant electrical consumption that are available to researchers in this field. To address this, new measurements were performed and combined with data emanating from an earlier study to provide a database of annual measurements for 23 houses at a 1-minute resolution that characterizes whole-house, non-HVAC, air conditioner, and furnace fan electrical draws, as well as the draw patterns of some major appliances. All houses were located in Ottawa, Canada. The non-HVAC measurements of this 23-house sample were shown to be in agreement with published estimates for the housing stock. The furnace fan was found to be the most significant end-use. These high-temporal-resolution data of electrical demands in houses can be used by researchers to increase the fidelity of building performance simulation analyses of different micro-generation technologies in residential buildings.

Keywords: Electrical loads, Non-HVAC electrical loads, Appliances and lighting, Housing

1. Introduction

Power flow in the reverse direction caused by distributed generation is the main issue limiting PV penetration levels in existing electricity distribution networks [1]. As was noted by Castillo-Cagigal et al. [2], in the future as higher levels of PV penetration occur, it will be more important to consume the electricity produced by PV on-site and the current widespread practice of exporting electricity generated by PV to the local electrical supply network will become less attractive. This is also true for any micro-generation technology. Consequently, electrical consumption characteristics of occupants will play an increasingly important role in determining the performance of micro-generation systems.

Saldanha and Beausoleil-Morrison [3] pointed out that both the magnitude and the temporal distribution of non-HVAC electrical loads influence the operation of energy conversion equipment within the building and in the electrical supply network. Their work also demonstrated that efforts to synthetically derive non-HVAC electric loads (e.g. references [4, 5, 6, 7, 8, 9]) may not adequately capture either the temporal variability nor the variation between households observed in the measurements.

Saldanha and Beausoleil-Morrison [3] summarized some of the past efforts in measuring and characterizing residential electrical demand patterns, such as those of Pratt et al. [10], Parker [11], Firth et al. [12], Knight and Ribberink [13], and Isaacs et al. [14]. Of these past efforts, the finest temporal resolution of gathered data was achieved by Firth et al. [12] and Knight and Ribberink [13] (who sampled

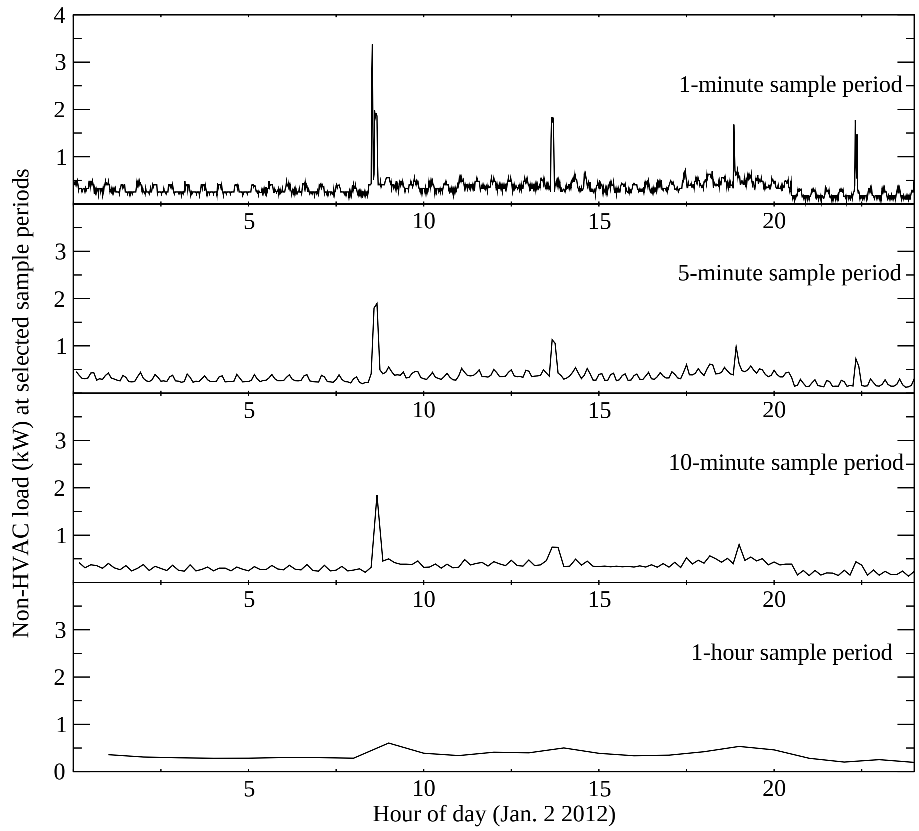

Figure 1: Non-HVAC profile of one volunteer (H15) for a single day shown at various sample periods

the electric consumption of 72 houses in the U.K. at 5-minute periods) and Isaacs et al. [14] (who sampled the electric consumption of 400 houses in New Zealand at 10-minute periods).

Although references [12, 13, 14] had robust samples, the major limitation of these works was that the temporal resolution of the gathered data was too coarse to accurately represent the magnitude of some peak loads. Figure 1 is shown to better illustrate this limitation.

In Figure 1, the non-HVAC profile that was measured for one of the volunteers of this present research is shown for one sample day. This profile is plotted four times at increasing sample periods (from top to bottom) to demonstrate the effect that temporal resolution of this type of data has on the magnitude of observed peak loads. Longer sample periods were obtained by averaging the 1 minute-timescale resolution data over longer periods. As can be seen, by increasing the sample period from 1 to 5 minutes, the observed peak load that occurs near hour 7 of the day has been dramatically reduced from approximately 3.5 kW to 2 kW. This effect is further exacerbated when the sample period is further increased to 10 minutes and 1 hour. Note that 5 minutes was the previous best sample period achieved by Firth et al. [12] and Knight and Ribberink [13].

To address this knowledge gap, Saldanha and Beausoleil-Morrison [3] provided new measured data on the electrical consumption of 12 Canadian houses sampled at 1-minute periods for an entire year. They argued that high-temporal-resolution data are required to increase the fidelity of building performance simulation analyses and to better support the study of innovative energy conversion systems (micro-cogeneration, on-site renewable electricity production, etc.). Cetin et al. [15] have also gathered end-use data at a 1-minute timescale resolution from 40 houses in Texas (United States).

To further demonstrate that there is a demand for this type of data, several other researchers ([16],[17],[18] and [19]) have supported their work with these data provided by Saldanha and Beausoleil-Morrison [3]. A thorough literature review of all studies in this field was performed by Rowlands et al. [20]. They concluded by identifying that generating this type of additional electricity end-use data is a research priority going forward which indicates that the demand for this type of data is not yet satisfied.

1.1. Contributions

The purpose of this research is to improve the understanding of residential electricity consumption patterns at a high temporal resolution primarily to enhance the fidelity of building performance simulation based research efforts of micro-generation systems. Particular emphasis is given to the improving the understanding of non-HVAC consumption patterns because in this field HVAC consumption patterns are often simulated.

For this purpose, the current article builds upon the work of Saldanha and Beausoleil-Morrison [3] by gathering new measured high-temporal-resolution data on an additional 11 Canadian houses and making them available to other interested researchers.[1] These new measurements are predominantly from more recently constructed houses of row-house design compared to the houses sampled by Saldanha and Beausoleil-Morrison [3] that were predominantly of single-detached design and of older vintages. This current work is an expansion of a paper initially published in a conference [21].

The article first describes the methods used to gather and process these data in Section 2. These data are then combined with those of Saldanha and Beausoleil-Morrison [3] to provide a database of annual measurements for 23 houses at a 1-minute resolution that characterizes whole-house, non-HVAC, air conditioner (A/C), and furnace electrical draws, as well as the individual draw patterns of some major appliances. Also in Section 2, some characteristics potentially rele-

[1] Interested researchers are invited to contact Ian Beausoleil-Morrison for access to any of these load profiles (ian_beausoleil-morrison@sbes.ca).

vant to electricity consumption (number of occupants, age, size) of the sampled houses are described to demonstrate the range of these characteristics contained within the sample.

For this database to be useful for its purpose, it is important to understand how well the 23 house sample represents the population. In Section 3, data from these 23 houses are compared to aggregate data representing Ontario's residential sector to demonstrate how well the sample reflects the annual electricity consumption of the population. In Section 4, the percentages of total consumption that occur within Ontario's time-of-use periods for these data are compared to estimates for the entire residential sector.

Aside from being a useful tool for building performance simulation, data from these 23 houses can be used on their own to improve the understanding of electricity consumption patterns at a high-temporal resolution. As a case study, in Section 5 some analyses are performed to characterize the draw patterns of some major end-uses before conclusions are finally drawn in Section 6.

2. New measurements

2.1. Methods

The electrical demands of 11 houses in the Ottawa area were measured beginning in the summer of 2011 for approximately 1 year. The experimental apparatuses that were used by Saldanha and Beausoleil-Morrison [3] were recommissioned for this research. For each of the 11 houses the total electrical import from the grid was monitored with 50 A current transformers (CT), whereas 30 A CTs were used to measure individual circuits (refer to Section 3 of reference [3]). As documented in detail in that earlier study, with this instrumentation

Table 1: Characteristics of the 11 houses monitored in this study

Label	Type	Vintage [a]	Size (m^2)[b]	Occupants
H13	mid	2010s	180	2
H14	mid	2010s	150	2
H15	mid	2000s	185	1
H16	mid	2000s	155	2
H17	mid	2010s	180	2
H18	mid	1990s	130	2
H19	mid	1970s	125	1
H20	end	1970s	125	2
H21	end	1940s - 1950s	150	3
H22	mid	2000s	150	2
H23	mid	1990s	180	2

[a] Decade of construction.

[b] Approximate floor area of liveable space, including finished portion of basement.

the average power draw over each 1-minute logging interval could be resolved to within 45 W (30 A CTs) or 75 W (50 A CTs) over a wide range of power draws and with a bias error of 2% or less on the derived electrical energy consumption.

All 11 houses were of a row-house design with full basements. The type, vintage, size, and number of occupants of each house is provided in Table 1. Whether a particular row-house was attached on one (end-unit) or two (mid-unit) sides is indicated by its "type" column in Table 1. Each house is identified with a label in this table. As the houses monitored by Saldanha and Beausoleil-Morrison [3] were identified as H1 through H12, the newly measured houses have been labelled H13 through H23. All houses used natural gas as the primary heating fuel and for domestic hot water heating, and all but one (H21) had central A/C for cooling. A single house employed an auxiliary electric space heater in its basement. All houses also contained a range (cooker), fridge, dishwasher, microwave, clothes washer and dryer.

Each house's total electricity draw from the grid was measured. The power drawn by the circuits supplying the furnaces (controls, ignition system, air circulation fan) and by the circuits supplying the A/Cs (compressor, condenser fan, controls) was also measured. Note that when cooling was provided, power would be drawn by both the A/C circuit to power the cooling device as well as by the furnace circuit to distribute the conditioned air to the house. Additional circuits were monitored in some of the houses:

- The electric range (cooker) was monitored in house H13 (full year), H14 (full year), and H15 (9 months).
- The electric clothes dryer was monitored in house H13 (full year), H14 (full year), and H15 (9 months).
- The dishwasher was monitored in house H13 (10 months) and H14 (full year).
- The auxiliary electric space heater in house H18 was monitored from October 15, 2011 until March 31, 2012 (169 days).

It was not feasible to measure these additional circuits in all houses due to the available number of apparatuses. Also, the measured end-uses were restricted to

Table 2: Numer of records that required data filling to create processed annual files

Label	**Filled Records**	
	Number of minutes	**Fraction of year**
H13	7359	1.4%
H14	36097	6.9%
H15	240	<0.1%
H16	18750	3.6%
H17	60	<0.1%
H18	8712	1.7%
H19	7236	1.4%
H20	29611	5.6%
H21	57	<0.1%
H22	25974	4.9%
H23	1489	0.3%

those end-uses that were powered from a separate circuit that could be separately monitored. Lighting, for example, was an end-use that could not be directly measured since all houses in this study had several electrical circuits that contained not only lighting, but various plug-in end-uses as well. The methods described in detail by Saldanha and Beausoleil-Morrison [3] were utilized to derive non-HVAC power draws (the sum of major appliances, lighting, and plug loads) from the measurements, to treat missing time records, and to eliminate some measurement artefacts in cases of very low power draws.

As in this earlier study, these data from houses H13 to H23 have been archived in two formats to make them available for future research. The first format includes the average power draw of each measured circuit over each 1-minute interval. These data are made available for each house's total monitoring period, although there are some missing records due to interruptions that occurred when the data loggers were out of commission.

In the second format of archived files, these data have been processed to facilitate future analyses and for use in building performance simulations. These files include the derived non-HVAC electricity draws as well as data from the individual circuits. Each file includes a full year's worth of data at 1-minute intervals. To compose these, missing records were filled as mentioned above. In cases where individual appliances were monitored for only a subset of the year (H13 and H15), the missing periods were filled with data from other periods to ensure complete annual files. For all cases, the periods selected to fill missing data were from the nearest day, at the same time of day, where data were not missing. The advantage of this technique was that the periods selected to fill missing data contained similar seasonal occupant behaviour as the periods of data that were missing. The technique that was used to fill missing records was described in more detail in Saldanha and Beausoleil-Morrison [3]. The number of records from each of the 11 houses that were filled is indicated in Table 2. All analyses subsequently reported in this article are based upon this second format.

2.2. Variations between houses

These new data from houses H13 to H23 were combined with data provided by Saldanha and Beausoleil-Morrison [3] (houses H1 to H12). A wide range of annual consumption levels between homes was observed for the combined set: 7.7 to 39.5 GJ for non-HVAC loads; 0.8 to 13.1 GJ for furnace circuit; and 0.1 to

4.8 GJ for A/C circuit.

To further describe the various measured non-HVAC consumption levels, a k-means algorithm [22] was used to cluster the homes according to each home's measured yearly non-HVAC consumption. In this iterative algorithm, a number of cluster centre values are determined and each house is associated with the centre whose value is closest to the house's consumption. For this application, only the values of three centres were sought after that represent low, medium and high non-HVAC consumption levels. The result is shown in Table 3 and reveals that the newly gathered data are most often associated with the low consumption level (H15, H17-H20, H22 and H23) while the original data are mostly clustered into medium (H1, H3-H7) and high (H9-H12) consumption levels. This is an indication that the newly gathered data represent lower consumption levels than were in the original sample.

The necessity of gathering measured high-temporal-resolution data from a larger sample of houses is also demonstrated by Figure 2. This plot shows the average non-HVAC power consumption of each of the monitored houses as solid markers. Note that these data were unavailable for house H8. The standard deviations observed from these measured data at increasing sample periods (1, 5, 10-minutes and 1-hour) are represented by the four different sizes of error bars. Shown to the far right of Figure 2 are statistics for "All" houses that represent values for the aggregate of the entire sample of houses.

As can be seen from Figure 2, significant differences are observed between the average values and standard deviations of non-HVAC power consumption of the individual houses. This shows that the characteristics of this type of data vary dramatically between houses and larger sample sizes are necessary to describe

Table 3: Clustering of homes according to yearly non-HVAC consumption using a k-means algorithm [22]

non-HVAC Consumption Level	**Cluster Centre (GJ year^{-1})**	**Houses**[a]
Low	10.6	H2,H15,H17,H18, H19,H20,H22,H23
Medium	18.0	H1,H3,H4,H5,H6, H7,H13,H14,H16
High	33.4	H9,H10,H11,H12,H21

[a]non-HVAC consumption not measured for H8

these variations.

It can also be seen that longer sample periods can significantly reduce the spread (standard deviation) of this type of data because peak draws of high magnitude and short duration are averaged to lesser values over longer sample periods as was observed in Figure 1. These additional data gathered from houses H13 to H23 provided by this research ensure that the combined data set of 23 houses has a greater statistical significance and should better represent the behaviour of the population at a 1-minute resolution.

2.3. Significant predictors of annual consumption

The differences observed between the consumption patterns of the 23 houses observed are due to a variety of factors relating to climate, house construction and occupant characteristics. Information describing some of these characteris-

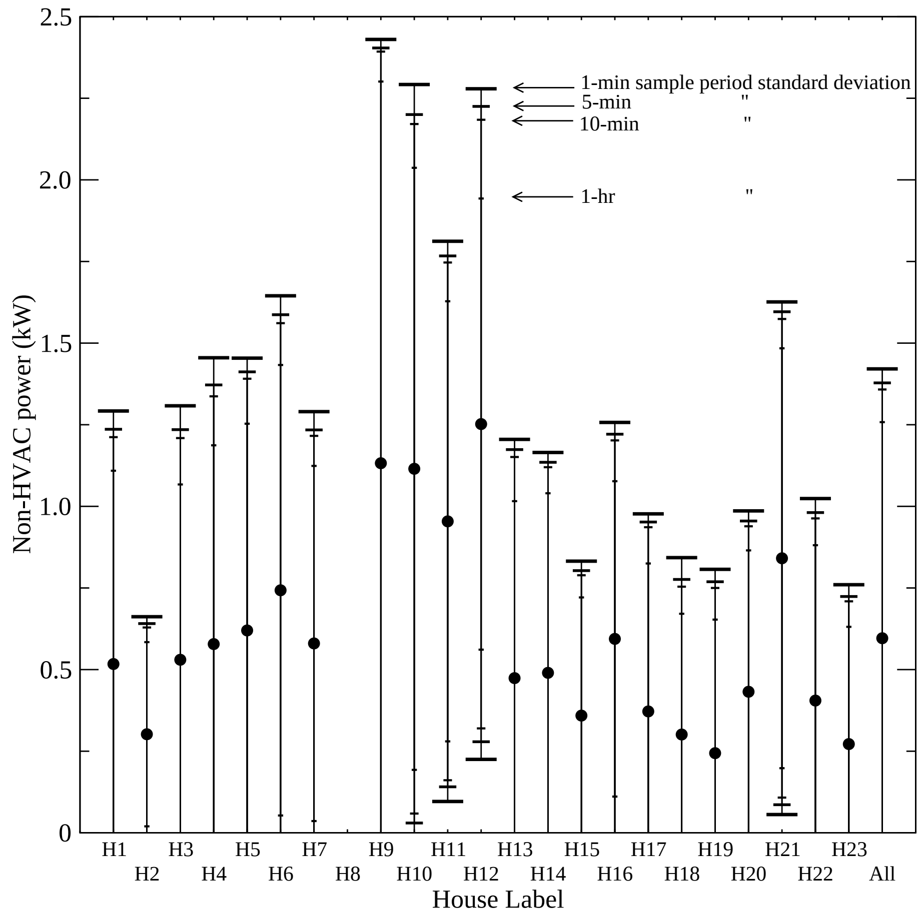

Figure 2: Average non-HVAC power consumption of each sampled house (if available) and standard deviation for data gathered at various sample periods

tics (number of occupants, house size and age) was available for each of these 23 houses. In this section, the relationship between these characteristics and electricity consumption is further investigated to demonstrate that this 23 house sample describes a reasonably broad range of these factors and electricity consumption values.

To determine the degree that different characteristics affect total annual electricity consumption, a multiple linear regression significance test was performed based on information that was available for each of the 23 houses in the sample. A detailed description of this type of test is given by Kutner et al. [23]. For this test, a linear function to regress the annual electricity consumption of the total, non-HVAC, furnace and A/C categories based on several variables was assumed,

$$E_i = \beta_0 + \beta_1 \cdot X_1 + \beta_2 \cdot X_2 + \beta_3 \cdot X_3 \tag{1}$$

Where E_i is the annual electricity consumption (GJ) of a specific category, X_1 is the number of occupants in a house, X_2 is the age of the house relative to 2010 (years), X_3 is the size of the house (m^2), and β_i are the coefficients determined through regression. These values of β_i determined from a linear regression are shown in Table 4.

The results of the significance test are the p-Values shown in Table 4. The p-Value is defined as the probability that the null hypothesis can produce a sample as extreme as the one observed. The null hypothesis for each p-Value is defined as equation 1 where the corresponding β_i coefficient has been set to zero. Therefore, the lower the p-Value for a coefficient, the more significant the variable that it modifies is for predicting annual consumption. From Table 4 it can be seen that the number of occupants has the lowest p-Value for the total and non-HVAC cate-

Table 4: Multiple regression coefficient hypothesis test

	Total		**Non-HVAC**		**Furnace**		**A/C**	
	β_i	**p-Value**	β_i	**p-Value**	β_i	**p-Value**	β_i	**p-Value**
β_0	-8.026[a]	0.416	-8.636[a]	0.19	-0.569[a]	0.85	1.7571 [a]	0.179
occupants	7.498[b]	0.017	6.617 [b]	0.002	0.4406[b]	0.613	-0.0037[b]	0.992
age	0.061[c]	0.562	0.0931[c]	0.224	-0.0317[c]	0.334	-0.0153[c]	0.284
size	0.085[d]	0.053	0.0576[d]	0.050	0.0250[d]	0.057	0.0041[d]	0.456

[a] GJ year^{-1}

[b] GJ year^{-1} occupants^{-1}

[c] GJ year^{-1} age^{-1}

[d] GJ year^{-1} m^{-2}

gories and is likely the strongest predictor, of the variables that were examined, for annual consumption. House size may or may not be a predictor (p-Value = 0.053 and 0.050) for these two respective categories, but is likely less significant than the number of occupants. For annual furnace consumption, house size was potentially the only significant predictor (p-Value = 0.057). The p-Value associated with house age was high for all annual consumption categories and is likely not a significant predictor of any of them. All characteristics had high p-Values for the A/C category, therefore, these characteristics are not likely significant predictors of annual consumption for this category.

There are a variety of characteristics that were not included in the analysis in Table 4. Environmental characteristics (outdoor temperature, solar insolation, wind speed, etc.) are very significant to the yearly consumption of the A/C and furnace and, therefore, to the total consumption as well. Other building construction characteristics (building orientation, fenestration area, building envelope insulation levels, etc.) are also significant to these categories. Even occupant behavioural characteristics (thermostat setpoint, usage of natural ventilation, furnace fan operational mode, etc.) could strongly affect these categories. In comparison, it is logical to assume that there is a much weaker link between the non-HVAC consumption category and either environmental or building construction characteristics as this category is not as directly affected by the thermal comfort of occupants. Since the major objective was to produce non-HVAC load profiles to support building performance simulation based research, an analysis that considered environmental characteristics or more in-depth building construction characteristics was considered outside of the scope of this research.

3. Comparison to housing stock

This section contrasts data from the 23 monitored houses to data published by Natural Resources Canada (NRCan) for the Ontario housing stock [24, 25] to demonstrate the statistical validity of the 23 house sample. NRCan draws upon published aggregate data on residential energy use and then employs stock accounting modelling methods along with data drawn from industry associations and external studies to estimate the disaggregated energy end-uses in a number of categories.

The database of 23 houses includes annual consumption data for the following end-uses: non-HVAC (22 houses), A/C circuit (22 houses), furnace circuit (23 houses), range (6 houses), clothes dryer (5 houses), and dishwasher (4 houses). These data are presented as box plots in Figure 3. The band inside each box is the median of that end-use, while the bottom and top of a box indicate that end-uses' first and third quartiles, respectively. The ends of the whiskers represent the min-

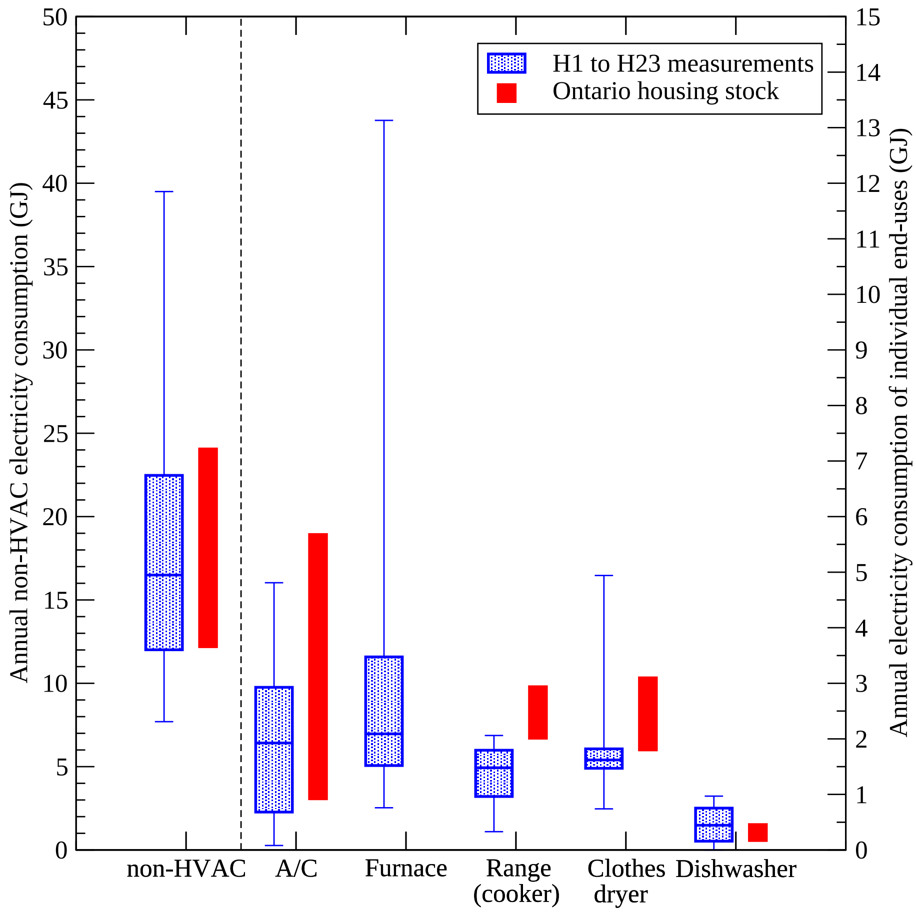

Figure 3: Distribution of annual electricity end-uses of monitored houses and comparison to NR-Can data for Ontario housing stock

imum and maximum, respectively, of each end-use. The non-HVAC electricity consumption is plotted using the vertical scale on the left of the graph, whereas the end-uses of individual appliances are plotted using the vertical scale on the right of the graph.

Figure 3 also plots NRCan's estimates of the disaggregated electricity consumption of these end-uses for Ontario's housing stock from 1990 to 2013. These were determined by dividing the NRCan stock estimates for Ontario by the number of housing units in the province. The NRCan data for each end-use spans a range because of technology and usage changes with time, and because the NRCan stock model takes into account the influence of year-to-year weather variations.

The presentation of Figure 3 allows a direct comparison between the measured data and NRCan's stock estimates. However, the shortcomings of this comparison must be recognized. For example, for the A/C end-use the box plot contains the measured data from the 22 houses that had central A/C. Whereas the NRCan data show the estimated A/C electricity consumption for the average Ontario house. As NRCan does not publish data on the number of Ontario houses with A/C, their data could not be normalized by houses with A/C. Notwithstanding these deficiencies, some interesting observations can be made from Figure 3. For example, the non-HVAC electricity consumption of half of the measured houses (i.e. quartiles 1 to 3 that are represented by the box) are in close agreement with the range of NRCan stock data. Furthermore, the median value of the measured non-HVAC consumption is close the middle of the range of the NRCan stock data.

It can also be seen that the measured A/C consumption tends to be less than the NRCan stock estimates. This is somewhat surprising given the earlier observation on how the NRCan data are represented in the figure. Recall that the figure plots the estimated A/C electricity consumption for Ontario houses normalized by the number of homes. Given that not all Ontario homes have A/C, one would expect that the NRCan data would be lower than the measurements, but the opposite is the case. There are a number of possible explanations for this observation: differences in climate conditions between the monitoring period and location and the stock data; or, differences in the occupant behaviour (e.g. use of shading, ventilation, and other measures to minimize the use of A/C) between the monitoring sample and the NRCan stock modelling.

Figure 3 also reveals that the measured data show lower range and clothes dryer electricity consumption than the NRCan stock data. However, it must be cautioned that the measured data are based upon limited sampling (6 ranges, 5 clothes dryers).

It can also be observed from Figure 3 that the A/C, range, and clothes dryer all contribute significantly to the annual electricity consumption, although the most significant single end-use is the furnace. The electricity consumption of the furnace was particularly high for 5 houses (H7, H9, H10, H13 and H16).

High furnace fan annual electricity consumption was caused by fans that were either active for long durations or fans that drew electricity at high rates. A detailed analysis of the furnace fan and A/C operating characteristics for all of the houses revealed that H7, H9 and H10 had active fans for long durations (65.5%, 100% and 100% of the year). Although H13 and H16 had active fans for comparatively modest durations (40.7% and 35.1% of the year respectively), the annual furnace fan electricity consumption of these houses was still high because their furnace fans drew electricity at high rates (0.594 kW and 0.550 kW respectively when active) as will be shown later in Figure 6.

4. Time of Use Consumption Patterns

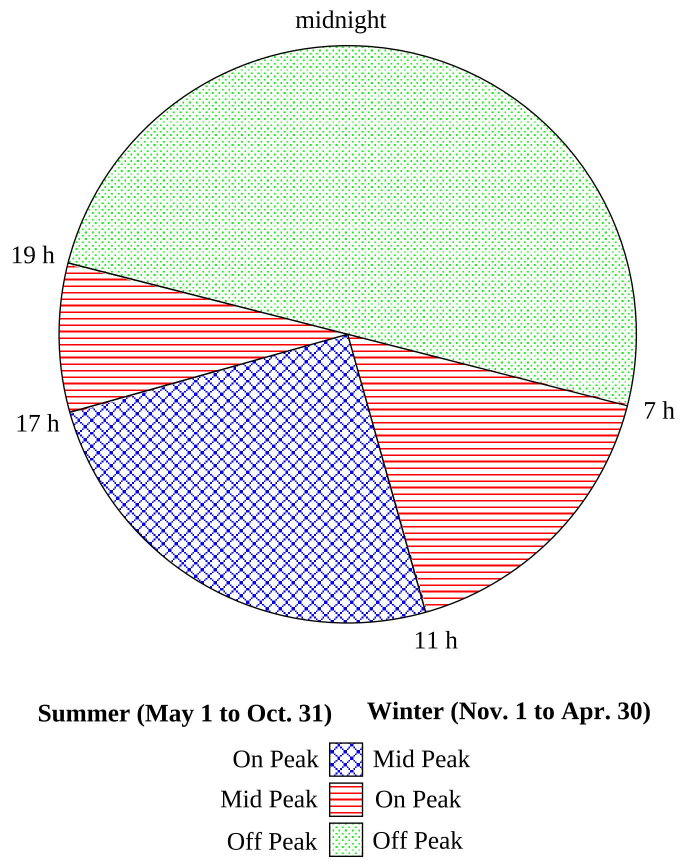

Figure 4: Ontario's time-of-use pricing scheme's on-peak, mid-peak, and off-peak periods

Both the magnitude and the temporal distribution of electricity demand patterns are significant from the perspective of the electricity supply network. To this end, many jurisdictions, including Ontario, have implemented time-of-use (TOU) pricing schemes to incent homeowners to shift their electricity consumption from periods of high demand on the electricity supply network to periods of lower demand. Ontario's TOU billing periods in 2011 for weekdays (Monday through Friday) are illustrated in Figure 4. As can be seen, the on-peak and mid-peak periods vary by season. Weekends (Saturday and Sunday) and statutory holidays are treated as off-peak periods. An analysis of the measured data from the 23 houses for the full year period revealed that 18% of the electricity consumption occurred during the on-peak periods, 17% during mid-peak periods, and 65% during off-peak periods. These observations are consistent with provincial-wide data which show that 18% of Ontario residential consumption occurs on-peak, 18% mid-peak, and 64% off-peak [26].

Figure 5 uses box plots to examine in greater detail the distribution of each house's electricity consumption in the summer and winter TOU billing periods. The band inside each box represents the house with the median fractional consumption in a given TOU billing period. The bottom and top of the boxes represent the first and third quartiles, while the ends of the whiskers represent the extreme values. As can be seen, the TOU consumption patterns vary significantly between individual houses. This figure also shows that greater consumption tends to occur during the summer mid-peak period than during the winter mid-peak period.

5. Case study: Significant end-uses

Statistics characterizing the end-uses that were monitored for each of the 23 houses are summarized in Figure 6. The markers in Figure 6 indicate the mean power draw that was measured for a specific end-use for an individual house when the specific end-use was active. For the purposes of this analysis, an end-use was

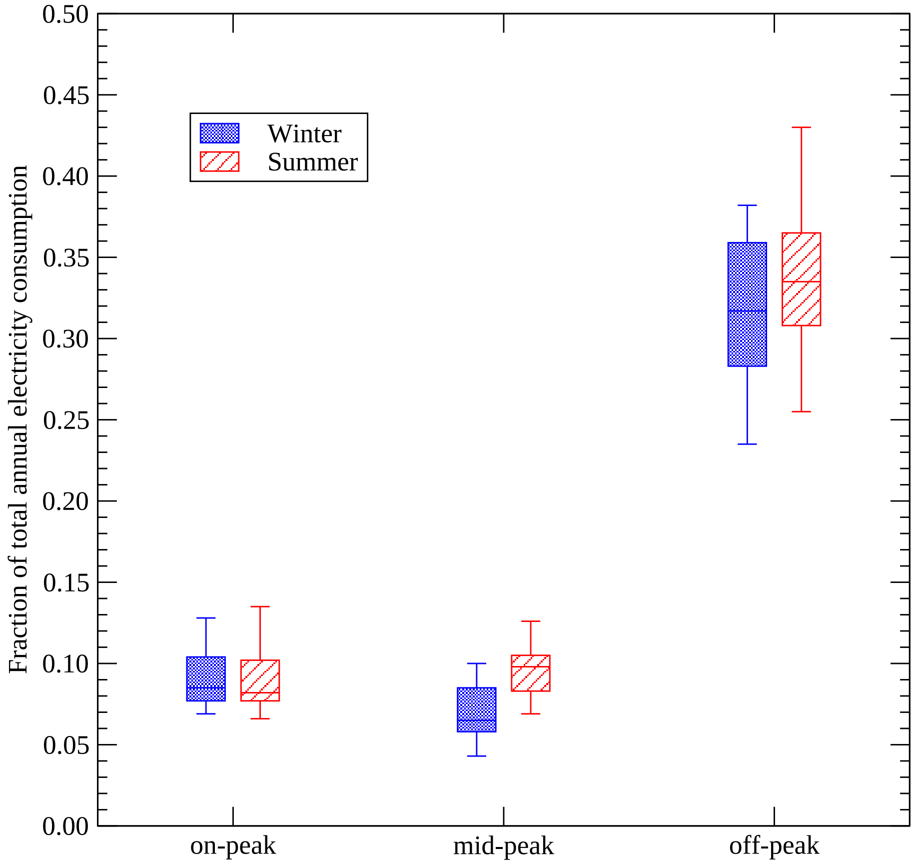

Figure 5: Distribution of TOU consumption patterns of measured houses

considered active if its measured power draw was 45 W or greater for 2 consecutive minutes. This definition was necessary to respect the resolution of experimental apparatuses previously described. The error bars represent the standard deviation of an active end-use.

Also shown, to the far right, in Figure 6 are statistics for “All” houses. The means and standard deviations for end-uses shown here were calculated from the aggregate set of active loads for a specific end-use from all houses where this end-use was monitored. For example, the dishwasher was only monitored for H12-H15, therefore, the set of active dishwasher loads is the aggregate of active dishwasher loads from houses H12-H15. Note that the dishwasher from H15 was most active so the mean calculated from “All” houses is heavily weighted towards H15.

When compared to similar sized non-HVAC end-uses, HVAC end-uses draw electricity in a more consistent manner. For example, “All” A/C systems drew a similar mean but lower standard deviation compared to the range. “All” furnace fans drew a similar mean but lower standard deviation compared to the dish washer. This suggests that there is greater variability in the manner non-HVAC end-uses consume electricity compared to HVAC end-uses.

A number of the 23 houses’ monitored appliances had significant power draws when operating. “All” clothes dryers and A/C drew a mean of 2.9 kW and 1.4 kW respectively.

6. Conclusions

To improve the knowledge of consumption patterns, end-uses, and temporal variations of electrical loads in the important residential sector, new measurements

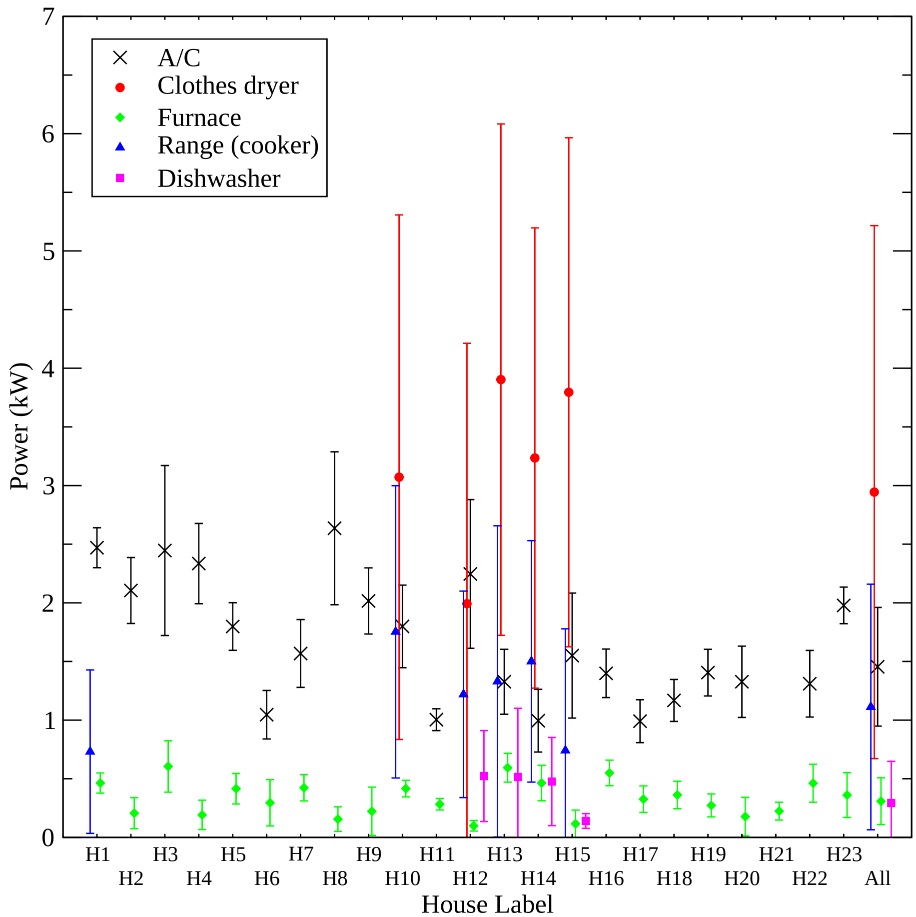

Figure 6: Average consumption by end-use for each of the measured houses

were taken in 11 houses located in Ontario (Canada). These have been combined with data emanating from an earlier study to provide a database of annual measurements for 23 houses at a 1-minute resolution that characterizes whole-house, non-HVAC, A/C, and furnace electrical draws, as well as the draw patterns of some major appliances. These data have been documented and archived in two formats to make them available to researchers to support their studies of other micro-generation systems. These data may be used as occupant load profiles in building performance simulations or for other case-study analyses (e.g. further study disaggregation of loads according to season, examine the correlation between occupant loads and environmental variables, investigate the complementarity of loads and the availability of renewable energy, etc.)

The high-temporal-resolution data provided by this research have been shown to more accurately characterize short-duration peaks in demand that occur in residential electric consumption profiles than previous efforts could. The major contribution of this work has been to increase the number of high-temporal-resolution residential demand profile data sets available to researchers from 12 to 23 and demonstrate that this larger sample reflects some important characteristics seen in the larger population.

7. Acknowledgment

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