ANALYSIS OF ELECTRICAL LOADS OF CANADIAN RESIDENCES AT ONE-MINUTE INTERVALS

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ABSTRACT

While whole building simulation tools have been developed to accurately model thermal demands on residential dwellings, they rely heavily on accurate representation of occupant behaviour and appliance usage to do so. This is evermore important during the cooling season in Canada where occupant's air-conditioner usage depends on several factors. To this effect air conditioning and non-HVAC usage of twelve typical Canadian dwellings in Ottawa, Ontario were measured over the summer of 2009 at one-minute intervals. The non-HVAC data was compared to previously generated synthetic profiles to assess their potential in representing typical Canadian occupancy usage as well as to provide more information regarding Canadian residential electricity consumption. This paper presents the results of this survey and recommends an alternate method of representing non-HVAC electrical demands input in building simulation.

INTRODUCTION

In Canada, residential energy usage accounts for 16% of total secondary energy use in 2006. Of this, electricity accounts for nearly 40% of energy use by end use (NRC, 2008). In 2007 coal accounted for 76% of all fossil fuels consumed to generate electricity in Canada (Sta, 2007) and 28.3% of said electricity went towards residential usage (NRC, 2008).

Typical residential electricity profiles have small base loads with short peaks of very high demand due to air-conditioning and appliance usage (Beausoleil-Morrison, 2008). These peaks arise from coincidental use of appliances for meal preparations, laundry and other daily occupant functions (Knight et al., 2007). In some regions such as Ontario, peak demand is often met by generation from fuels with high global warming potentials (GWPs) such as coal or costly fuels such as natural gas. This is illustrated by data collected from the Independent Electric Systems Operator (IESO) of the overall market demand in Ontario and the supply by generation technique over a particularly hot summer's day in 2008, as shown in figure 1.

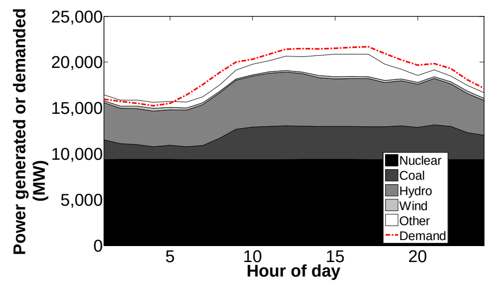

Figure 1: Market demand and supply by generation source in Ontario on June 7th, 2008 (data sourced from (IES, 2009)). Note: "Other" indicates gas fired and wood waste sources.

This shows that generation from coal and gas are two major load followers and contributors of greenhouse gas emissions. Residential space cooling and appliance usage are significant causes of these peak demands.

Daily load factors are the average power demanded over a given day divided by the maximum. Low daily load factors indicate grid inefficiencies of requiring extra power generating capacity for only portions of the day from peak demand. The load factor for the day in figure 1 was 0.876 (data sourced from (IES, 2009)). Increases of up to 200% in transmission losses during peak demand (OPA, 2007) and decreases in plant performance on hot days result in further network inefficiencies. The Province of Ontario alone intends to increase its generating capacity in the near future and further improvements in production, transmission and distribution over the next two decades (OPA, 2007). Extra power generation capacity required from peak demand results in low daily load factors and poor grid efficiency.

By devising strategies to reduce peak demand from residential dwellings such as demand side management (DSM), micro-cogeneration or storage methods, electricity could be produced and transmitted in a more efficient manner. Utility providers could resort less to production from fuel sources with high GWPs and costly capacity expansion could be offset to other improvements within the grid.

Whole building simulation, non-HVAC loads and occupant intervention

Whole building simulation is showing to be a significant asset in buildings design. Simulation tools can assess new technologies to conserve energy or more efficiently produce and transmit electricity. These tools can accurately assess thermal and electrical demands on a building given accurate inputs for occupant activities such as appliance usage and solar gains from openings. These activities contribute to non-heating, ventilation and air-conditioning (non-HVAC) loads and passive thermal gains that vary widely depending on not only the size and location of the dwelling, but the habits, lifestyle and social status of its occupants (Knight et al., 2007). These contributions, typically input into simulation tools in the form of energy profiles, can have large effects on the overall thermal and electrical demands. While reliable methods exist to predict thermal and electrical-HVAC loads, accurate data to represent typical non-HVAC loads and methods to assess occupancy behavior for a wide spectrum of Canadian dwellings is lacking (Beausoleil-Morrison, 2008).

This lack of data makes it difficult to predict air-conditioning usage and cooling demands in building simulation and to assess new strategies. The results from Annex 42 of the International Energy Agency's Energy Conservation in Buildings and Community Systems Programme (IEA/ECBCS) showed the potential for residential cogeneration is highly reliant on these occupant factors (Beausoleil-Morrison, 2008). Further data regarding electrical usage of air cooling and appliance usage of Canadian dwellings is necessary to accurately draw conclusions from building simulations. With improved accuracy building simulation becomes a cost-effective approach to assess solutions to peak power demand from residential usage.

Work in collecting data of non-HVAC loads and producing synthetically generated energy profiles for different countries and climates have been previously attempted. These generally fall into two different categories as the source for profile generation: empirical data collection at the end user level (Widén et al., 2009; Haldi and Robinson, 2009) and bottom-up approaches derived from gathering of appliance penetration rates and average housing annual energy consumption (Capasso et al., 1994; Paatero and Lund, 2006). The empirical collection method, while more accurate in obtaining true load demands, is often difficult and expensive to collect and result in small sample populations with potentially large bias generally only fit towards a small demographic. Knight et al. (2007) noted that this approach may lack fine enough time step resolution to effectively capture electric loads. The bottom-up approach method obtains statistical data regarding total energy consumption by type or residence and appliance relatively easy however it relies heavily on the accuracy of the algorithm implemented to generate said profiles.

Both methods result in attempts to create profiles based on original data and use of stochastic randomly generated numbers. This requires the implementation of an algorithm to mimic occupant behaviour and appliance usage. Earlier methods in this began with works by Walker and Pokoski (1985); Gross and Galiana (1986) and developed recently into more sophisticated algorithms using fuzzy logic, genetic algorithms and neural networks (Alfares and Nazeeruddin, 2002). Paatero and Lund (2006) noted that these new algorithms may improve profile accuracy where detailed statistical data is outstanding.

Recently, work producing synthetically generated energy profiles for the Canadian stock of dwellings using a bottom-up approach was performed by Armstrong et al. (2009). This work developed energy profiles based upon average number of appliances within a dwelling and probabilities of usage time for different degrees of Canadian housings and social behaviours at five-minute intervals throughout the day. This work did not include air-conditioning profile usage in its development. The profiles produced were compared with another dataset collected by Hydro-Québec from 1994 to 1996. This data set measured non-HVAC electricity demand from 57 single detached homes at 15 minute intervals (Knight et al., 2007). Any attempt to generalize occupant behaviour into an algorithm, even a sophistication one, will ultimately lack the true complexity of occupant behaviour. The algorithms may capture idealized daily routine function accurately; however, real life is seldom routine. The ability to capture the complexity of when occupant behaviour is not ideal into an algorithm is an extremely difficult task and could significantly vary between dwellings. This point will be treated later in the paper.

The temporal resolution of the energy profiles is a crucial factor. An example of this is shown in figure 2 from (Armstrong et al., 2009), where the same electrical demand was produced using five-minute sampling rates and hourly averaged sampling rates. The hourly generated profile implicitly omits finer details and would lower the performance accuracy of a system designed to meet its demand. An acceptable temporal resolution to assess micro-cogeneration performance would be five-minute intervals. This interval length would observe the physics of a system with a sufficient level of resolution whilst conserving quasi-steady state assumptions used in modeling transient plant performance described by Beausoleil-Morrison (2006).

Figure 2 illustrates the necessity of having accurate load profiles at fine time resolution scales if the demand varies. The performance of a cogeneration device using the five-minute time steps would differ significantly more than the hourly time steps. For example, in the eleventh hour of the day a peak of approximately 2kW would have been neglected in the hourly approximation.

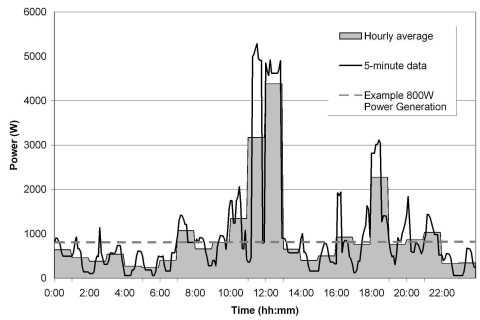

Figure 2: Comparison of typical electricity profile taken at 5 minute intervals and averaged over one hour intervals taken from Armstrong et al. (2009)

Beausoleil-Morrison (2009) observed that occupant intervention to control the temperatures within the home have significant impacts on space cooling. Space heating in colder months may be easy to predict and occupant intervention has little effect. However interventions such as opening and closing of windows, blinds, and shutters, and thermostat adjustments have significant impacts on cooling loads from passive solar gains during the summer. Measured data of space cooling in dwellings could be correlated to factors that govern how and when occupants cool their homes.

OBJECTIVES OF RESEARCH AND OUTLINE OF PAPER

A research project is underway to measure and analyze non-HVAC and space cooling electricity profiles of Canadian single family detached dwellings. In this way the non-HVAC profiles could offer insight into producing electrical load profiles of occupant living and appliance usage in building simulation. Assessments of new strategies in electricity production and transmission in Canada could be done in a more cost-effective manner. The space cooling data collected offers comprehension of when and how occupants choose to cool their homes from air conditioning units as opposed to or including window shading and openings. Ideally the results from the data gathered would provide a foundation for new algorithms to represent occupant efforts to mitigate space cooling during Canadian summer months.

In the context of this paper, the data gathered in this research represents an effort to better understand residential non-HVAC loads of Canadian dwellings and analyze their frequency distributions throughout the day. A comparison with previously generated synthetic profiles (Armstrong et al., 2009) assesses the ability of generated profiles to accurately represent the wide spectrum of Canadian dwellings. An alternate approach to developing randomly produced non-HVAC load profiles based on empirical data using techniques previously developed will also be discussed.

Category	Electrical Consumption (kWh/year)
Low	4157-6964
Medium	8844-10443
High	12045-19345

Table 1: Previous Annual Electric Consumption of Occupants

FIELD SURVEY OF NON-HVAC LOADS

Electrical usage data was measured in several houses throughout Ottawa, Ontario over the summer and fall of 2009 to gain a better understanding of how to accurately simulate residential dwelling performance. Twelve houses had monitoring devices measuring their overall electricity consumption, air conditioning consumption and air circulation fan consumption at one-minute intervals. The majority of these houses obtained space and hot water heating by other means than electricity. Thus, by measuring air conditioning and circulation fan consumption the true non-HVAC loads could be determined from the overall measurements.

The houses were selected in an effort to represent the wide spectrum of Canadian dwellings. Four houses were chosen based on previous annual electrical consumption to represent each low, medium and high energy single families in detached dwellings. The range of the occupants' annual electricity consumption for the year prior to measurement for each level of energy is summarized in table 1.

One participant in each category had an additional three electric appliances measured. These were the stove, dryer and dishwasher. The high end user who used electricity for DHW had this circuit monitored in lieu of their dishwasher.

The monitoring equipment was installed from the beginning of July 2009 and was to remain in the dwellings for one year. The occupants also completed a brief survey regarding their willingness to use shading and window openings to mitigate cooling loads throughout the day.

Data Analysis

By subtracting the air conditioning and furnace consumption from the overall house electrical consumption, the non-HVAC electrical consumption profiles could then be produced. As heating was obtained by means other than electricity, the non-HVAC consumption data sets would represent the electricity drawn by the dwelling for appliance usage and occupant uses such as lighting etc.

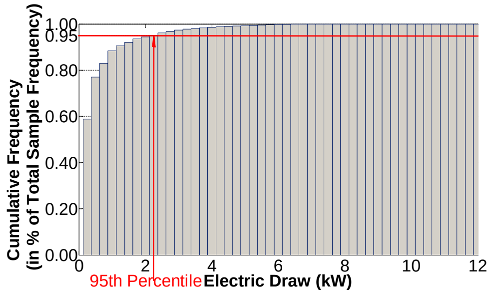

Figure 3: 95th percentile illustration from a cumulative histogram from the data survey

Measured Houses	Generated Houses
2.46	2.86
1.17	3.04
1.87	2.89

Table 2: 95th Percentiles in kW of three medium measured houses from survey and three houses generated by Armstrong et al. (2009)

The original logged data of constant power draw in Watts over the last minute was divided by the 95th percentile power draw of the data set. In other words, if every electric draw was arranged in a cumulative histogram similar to the one shown graphically in figure 3 illustrating a data set from the survey, the electrical draw where 95 percent of all the power draws would be found is the 95th percentile. By non-dimensionalizing the data sets, the results for each dwelling could be compared as fractions. This percentile was chosen over the maximum power draw because it was thought that such an occurrence may have been random and may not adequately represent a reliable datum.

The 95th percentile of both the measured medium energy households and the generated medium households from Armstrong et al. (2009) are summarized in table 2.

This suggests that the three houses from the survey have no relation to each other and their 95th percentile's do not necessarily compare. However the generated profiles from Armstrong et al. (2009) have 95th percentiles quite close to each other because they were derived using the same algorithm with the same target annual consumption. It should be noted that houses 1, 2 and 3 from the measured survey in no way relate to houses 1, 2 and 3 of the generated profiles from Armstrong et al. (2009) and were simply for labeling purposes.

The Province of Ontario intends to implement a time-of-use (TOU) system where during peak hours the cost of electricity is at a higher rate than during off-peak hours. The purpose of this is to give consumers a financial incentive to shift non-essential appliance activities such as clothes washing and drying to periods throughout the day of low demand. The latest price structure is shown in table 3. The optimal method of pricing this system and its benefits to consumer and utility provider continue to be assessed (OEB, 2007).

Table 3: Time-of-use pricing scheme for the province of Ontario, Canada, as of November 1, 2007 (OEB, 2007)

Time	Summer Hours (Aug 1-Oct 31)	Price /kWh	Winter Hours (Nov 1-Feb 28)	Price /kWh
Off-Peak	10 pm - 7 am weekdays; all day on weekends and holidays	3.5c	10 pm - 7 am weekdays; all day on weekends and holidays	3.4c
Mid-Peak	7 am - 11 am and 5 pm - 10 pm on weekdays	7.5c	11 am - 5 pm and 8 pm - 10 pm on weekdays	7.1c
On-Peak	11 am - 5 pm weekdays	10.5c	7 am - 11 am and 5 pm - 8 pm weekdays	9.7c

CT Size(Amps)	Watt-hours per pulse
30	0.750
50	1.250
100	2.5

Table 4: Watt-hours per pulse resolution in logging equipment of field survey

As such the measured data were organized by day type namely: weekday summer, weekend summer, weekday winter and weekend winter as taken from the definition by OPA's TOU program (OEB, 2007). Days where the monitoring equipment was malfunctioning or down for maintenance were removed from the dataset.

The equipment monitored multiple phases, where applicable, of voltage, current and the power factor sampling at a rate of four hertz and a logging interval of one-minute. These measurements were calculated into true energy consumed over the last cycle. Each current transducer (CT) had a specific threshold of energy consumption needed to produce a 'pulse' to the data logger. These values are shown in table 4. If the energy consumed over the last cycle was larger than the watt-hours per pulse resolution scale a pulse would be sent to the logger and a count would be registered over the last cycle.

These original datasets in terms of counts could be converted to average electricity drawn over the last logging interval using equation 1.

$$Power(kW) = 0.06 \cdot WattHoursPerPulse \cdot PulseCounts \quad (1)$$

The CTs were selected so as not to exceed the maximum amperage that the device it was monitoring would

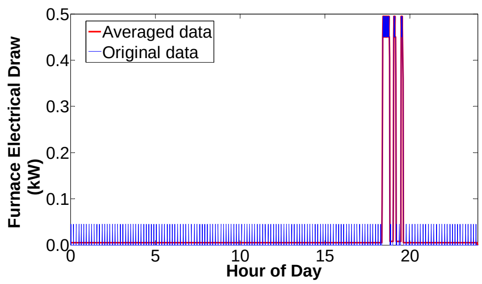

Figure 4: Example of data averaging as a result of too coarse of a measuring resolution for a one-minute timestep

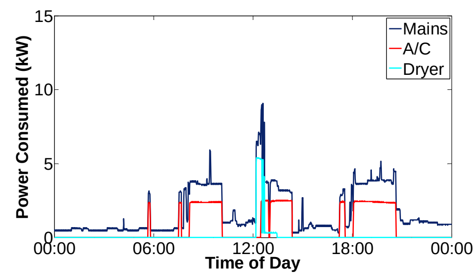

Figure 5: Household electrical energy usage for one of the medium-energy dwellings at one-minute interval on Aug. 11, 2009

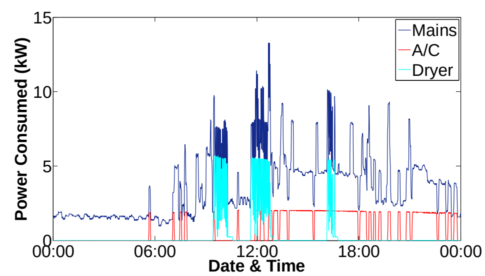

Figure 6: Household electrical energy usage for one of the high-energy dwellings at one-minute interval on Aug. 11, 2009

draw. In other words if the device would consume more than 240 pulses over a minute (the maximum number of pulses possible for a monitoring rate of four hertz) it would need a larger CT. Thus a CT could not be sized too small and not capture the amount of counts in full operation nor could it be too big and not measure any counts at all because the device was not drawing sufficient electricity to produce pulses. This introduced an issue for devices not in full operation drawing little power.

Devices drawing very low constant power appeared to draw no power over several minutes with sporadic minutes drawing instantaneous power in between. This was seen mostly in air conditioners and furnace fans when not in full operation.

This was rectified by identifying these periods and counting the occurrences of the instantaneous draws within a period. Identifying these periods was a matter of taking the original pulse count data sets and searching for occurrences of zeros followed by other zeros or a count of one. The number of ones of the period were then divided by the size entire interval to arrive at the average electricity drawn. This is shown graphically in figure 4.

Figure 4 represents a furnace fan in low power mode throughout the day except for a small period of operation. The data follows much more closely the true power draw of the furnace fan after averaging. While in operation, the electricity drawn fluctuates, again, due to the CT resolution. However, treating these would be exceedingly more difficult without removing significant power consumption draws.

RESULTS AND DISCUSSION

Figures 5 and 6 show the medium and high energy participant electricity consumption on a randomly selected hot day Aug 11, 2009 respectively. The figures show the house's overall electricity consumption labeled mains, the air-conditioner and the dryer. These two devices are the largest electricity consuming appliances within the household. It should be noted that \mains" is an aggregate of non-HVAC loads, air-conditioning loads and circulation fan loads.

From these figures, the variance in energy consumption between dwellings is apparent. The high consumption house has a baseload two to three times larger than the medium user over the day. Also, there is a significant increase of overall electricity draw on the household when the air conditioner and dryer are in operation, especially when they coincide. When both of these devices were in use along with the other household appliances, the overall house electricity draw increased from a baseload of approximately 0.7 kW to 9 kW in the medium usage house and 1.8 kW to 13 kW in the high usage house. These are clear examples of peak power demand in residential dwellings.

Figure 7 shows the medium-energy dwelling's average non-HVAC electrical draw as a fraction of their 95th percentile over every summer weekday plotted with two randomly selected days.

Figure 7 illustrates the detail lost in averaging days of data. This is because the energy peaks and lows tend to cancel one another and produce a trend with little variation with respect to its previous time step. Averaging inherently defeats the purpose of analyzing peak residential loads and are not good statistical point estimators of residential loads.

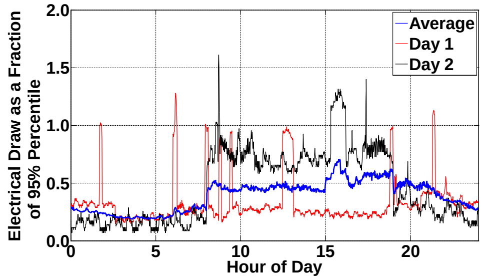

Figure 7: Average household daily electricity draw as a fraction of the 95th percentile with two random particular days

House	Mean	Standard Deviation
1	0.9192	0.0634
2	0.9066	0.0490
3	0.7906	0.1339

Table 5: Mean and standard deviations of power draw occurrences equal or less than 50 percent of the 95th percentile over each summer weekday of measured houses

Another approach is to produce histograms to analyze the distribution of electrical draws throughout the day over many days. Three of the four medium user data sets were arranged into normalized histograms to compare with the synthetically generated profiles from Armstrong et al. (2009). Figure 8 shows three medium normalized histogram distributions of the measured houses and the synthetically generated profiles from Armstrong et al. (2009) respectively over every summer week day.

In figure 8, each colour band represents one of the houses from the survey or the generated profiles. Each band is comprised of about 80 individual bars each representing a summer weekday. Each day is divided into ten bars representing the frequency of occurrence corresponding to the bins shown on the horizontal axis. For example, the first summer weekday day of the first house in the survey represented by the leftmost red bar had 59 percent of its electrical draws occurring between zero and half of its 95th percentile, 16 percent between half and one of its 95th percentile and 23 percent between one and 1.5 of its 95th percentile etc.

The bands also exhibit how much these values vary day by day. To quantify this, tables 5 and 6 show the mean and standard deviation of the measured and generated occurrences respectively, from the first bin . In other words it reflects the average and standard deviation of electricity draw occurrences that were equal or less than half of the data set's 95th percentile.

Once again it should be noted that houses 1, 2 and 3 from the measured survey in no way relate to houses 1,

House	Mean	Standard Deviation
1	0.9171	0.0553
2	0.9228	0.0530
3	0.9261	0.0461

Table 6: Mean and standard deviations of power draw occurrences equal or less than 50 percent of the 95th percentile over each summer weekday of generated houses

2 and 3 of the generated profiles from Armstrong et al. (2009) and were simply for labeling purposes.

In comparing these values, the synthetically generated profiles show less variance in power draw occurrence when compared to profiles from the field survey. Namely house number three from the survey has a much different distribution than houses one and two. Figure 8 also shows that the measured data has many more occurrences of peak power demand than those seen from the synthetically generated profiles. This was up to five times the 95th percentile in the case of measured house number two. The synthetically generated profiles show no occurrences of demand greater than three times the 95th percentile.

This indicates that while synthetically generated profiles may be excellent initial cost effective representations of Canadian dwellings, they may lack the complexity necessary to capture a wide spectrum. This shortcoming is inherent in algorithms that generalize random and widely varying occupant behaviour. This also indicates that the generated profiles do not exhibit the occurrences of higher peak demand that is seen is actual dwellings. A device simulated to alleviate peak demand with the generated profiles would never perform against the most crucial power draws. Business trips, vacations, relative visits, illness, children visiting from post secondary studies on weekends to do laundry were just some of the events that the occupants mentioned that deviated themselves from their regular routine. These are examples of the complexity and randomness of occupant behaviour that an algorithm cannot completely reproduce.

FUTURE WORK AND RECOMMENDATIONS

In order then to accurately represent the bulk of Canadian housing more extensively, we recommend exploring a new approach using the techniques discussed by (Hill and Melamed, 1995). This approach would use empirically measured data similar to that gathered in this paper and statistically analyze the distributions for means and variance. It would also analyze the correlation factors with respect to future time steps known as autocorrelation. An autocorrelation factor reflects the relationship between the variable at a present time step

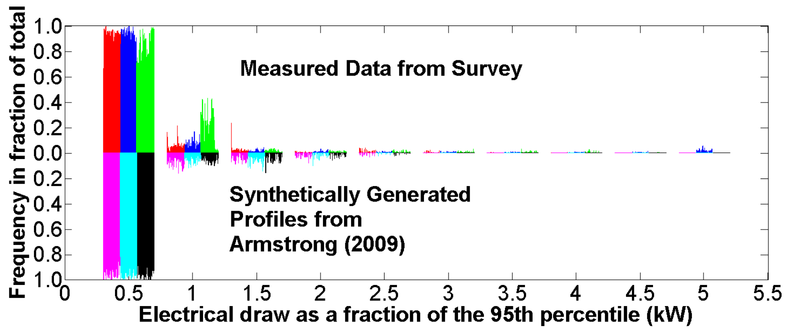

Figure 8: Comparison of normalized histograms of measured non-HVAC loads of three medium usage houses on summer weekdays with synthetically generated profiles from Armstrong et al. (2009). Colour bands red, blue and green on the top represent the three measured medium houses from the field survey compared with colour bands purple, teal and black on the bottom representing the three medium energy synthetically generated annual profiles from Armstrong et al. (2009).

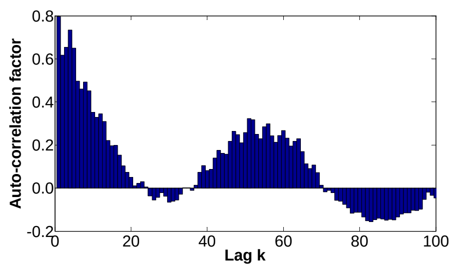

Figure 9: Auto-correlation as a function of lag k time steps during on peak hours for a particular day from the data set

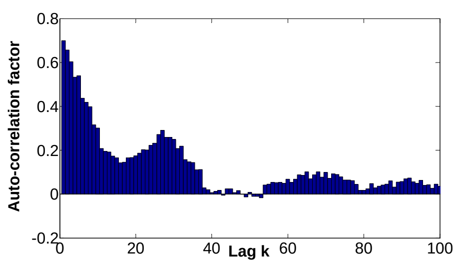

Figure 10: Auto-correlation as a function of lag k time steps during off peak hours for a particular day from the data set

and a future variable k time steps later. The value k is known as the lag.

$$ACF = \frac{\sum(x_i - \bar{x})(x_{i+k} - \bar{x})}{\sum(x_i - \bar{x})^2} \quad (2)$$

This could be applied for different times of the day as well as correlation to the current time of day to be able to produce statistically similar randomly generated profiles. Figures 9 and 10 illustrate this concept using a randomly selected day from the data set that has been divided into on peak and off peak times as defined in table 3 respectively.

In this way, as the cost of purchasing monitoring equipment has already been incurred more data can be continued to be collected into a database of gathered data; specific to the energy consumption, location, size, number of occupants etc. This could generate random statistically significant load profiles of a specific dwelling if desired or a general profiles based on the entire database.

New strategies such as DSM, storage and micro- cogeneration could be simulated with the general database with sensitivity analysis on specific houses to observe the potential in said cases. If the database could be randomly selected without bias new strategy potentials could not only be assessed but at what level of penetration they occur. This could have residual effects on pricing schemes and costs of implementation.

CONCLUSION

Whole building simulation, while able to accurately predict energy demands on dwellings, relies on precise non-HVAC electrical and DHW profiles. Occupant activities, appliance usage and space cooling demands in a Canadian context are outstanding and difficult to predict. New strategies in reducing peak power demand in residential dwellings using building simulation requires statistically significant non-HVAC electric load profiles representing a wide spectrum of Canadian dwellings.

A field survey of residential non-HVAC electric load profiles in the Ottawa, Ontario area was performed in 2009 to gain information for use in whole building simulation. This paper briefly presented some of the results and compared them with previously developed synthetically generated profiles.

As expected, dwellings with higher annual consumption's exhibited larger baseloads and peak demand than houses with less. It was also illustrated that averaging daily load profiles into one curve lacked useful information due to peak occurrences eliminating each other throughout the day. Arranging these days into histograms to observe the frequency of power draws over a day or even over a period of the day proved more valuable.

A brief comparison of the average energy occupants' load profiles on summer weekdays with previously generated synthetic load profiles from (Armstrong et al., 2009) indicated that synthetic profiles may lack the complexity to capture a wide spectrum of Canadian dwellings.

An alternate approach to developing energy profiles rather than the use of algorithms would be to employ statistical techniques discussed by (Hill and Melamed, 1995). These techniques would analyze collected data of energy consumption and randomly produce synthetic profiles that are statistically identical in the context of mean, variance and autocorrelation. In this way, as more data is collected into a database, profiles can be developed with greater statistical certainty. New strategies can be assessed against the general database and specific cases to determine the sensitivity of their performances.

ACKNOWLEDGMENTS

The authors are grateful for the funding provided by the Natural Research Council's Institute for Chemical Process and Environmental Technology, Natural Resources Canada and by Ian Beausoleil-Morrison's National Sciences and Engineering Research Council Discovery Grant.

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