NEW PROFILES OF OCCUPANCY DRIVEN LOADS FOR RESIDENTIAL SECTOR ENERGY DEMAND MODELLING

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ABSTRACT

Energy modelling is used by researchers to estimate aggregate energy consumption and time-step demand (power) of buildings. When considering new building technologies, time-step demand modelling plays an important role on several levels: 1) it allows homeowners and builders to determine viability within time-of-day energy and demand pricing schemes and smart-metering response; 2) it can help utilities accurately forecast short term loads so that they can procure sufficient capacity, especially with consideration of residences opting for new technologies that affect load profile; 3) it can inform the creation of energy policy to support implementation of technologies that may have a desirable effect on community load profiles.

Building simulation tools can address these issues by providing accurate energy consumption estimates for homes and communities. However, researchers often rely on a limited number of synthetically developed electricity and domestic hot water (DHW) load profiles and these do not permit comprehensive demand evaluation at a community scale. Recently, occupant load data has become available through electrical utility 'smart metering' programs, academic and industrial research endeavors, and municipal energy savings programs. Four separate datasets have been obtained for our research project:

- two datasets including 1-minute time-step DHW consumption measurements from 41 and 119 houses
- one dataset including 15-minute time-step whole-house electricity load measurements from 161 homes
- one dataset including 1-minute time-step disaggregated electricity load measurements from 23 homes

From these datasets, annual time-step DHW and electricity load profiles have been generated. To demonstrate the effect of using a variation of profiles, a community scale energy model is being created, utilizing a set of single-family detached house Archetype building models developed by the U.S. Department of Energy. This paper presents these new profiles and the initial stages of work completed to demonstrate the effect of using a variation of profiles on a community scale.

INTRODUCTION

In Canada, energy consumed by households' accounts for 17% of secondary energy use and 14% of GHG emissions (NRCan 2014). Energy use and GHG emissions reduction have become an international focus. The overall demand of the Canadian residential sector is projected to increase into the future as new homes are constructed; however, the energy-use per square metre of floorspace is expected to decline due to improvements in building construction practices (NEB 2013). For both new construction and retrofits, some builders will focus on implementing high performance building technologies at a community scale. Examples of such communities and community scale projects already exist in Canada (e.g. www.dlsc.ca and www.halifax.ca/solarcity/) and the Canadian federal government is currently funding a project to demonstrate the feasibility of building Net-Zero Energy Housing (NZEH) Communities in Ontario, Quebec, Nova Scotia, and Alberta with an aim to create a platform for the broader adoption of NZEH across Canada (NRCan 2015).

Time-step load of these communities can concern a range of stakeholders. For example, homeowners and builders will seek to understand the performance of various building technologies within time-of-day energy pricing schemes. Utilities require accurate short-term load forecasts to inform the selection of energy supply and distribution equipment. Building simulation tools such as EnergyPlus™ and ESP-r can be used to provide accurate time-step load estimates of electricity and thermal energy for buildings.

An important input to building simulation software are occupant driven load profiles, which represent loads that are greatly influenced by occupant behaviour rather than the natural and built environmental conditions. These loads can be divided into two primary categories: domestic hot water consumption (DHW) and appliance, lighting and plug loads (ALP). Inter-household variation of these loads is significant and is demonstrated by Figure 1 which shows the average hourly ALP load for 5 households.

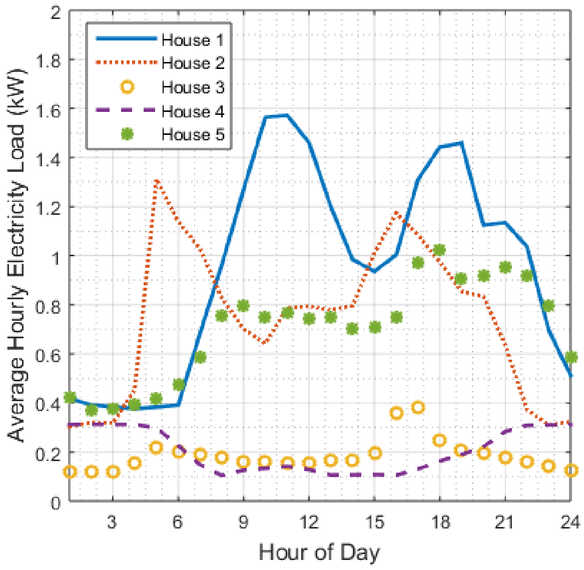

Figure 1 Examples of daily variations in household electricity load

Each house in Figure 1 demonstrates unique characteristics. Notably, they do not all 'peak' in load simultaneously. On average, one household may be characterized as a 'evening' user of electricity or DHW (e.g. House 1), or 'night-time' user (e.g. House 3). In evaluating the performance of various building technologies using building simulation, it is important to consider households with a variety of load characteristics, to insure that new technologies will perform as expected.

While ALP loads vary significantly between houses, generation technologies such as solar photovoltaic (PV), will be highly co-incident between houses as the sun shines on a whole neighbourhood. For this reason, the use of a variety of profiles is also necessary when using simulation to evaluate such a technology in a community scale application. Previous research focused on community-scale energy analysis has relied on a limited number of profiles, repeated for each house of a community (Swan et. al. 2011). While this may provide accurate aggregate energy results at a daily, monthly or annual scale, unrealistic load peaks (local maximums) and valleys (local minimums) occur. This is demonstrated by Figure 2.

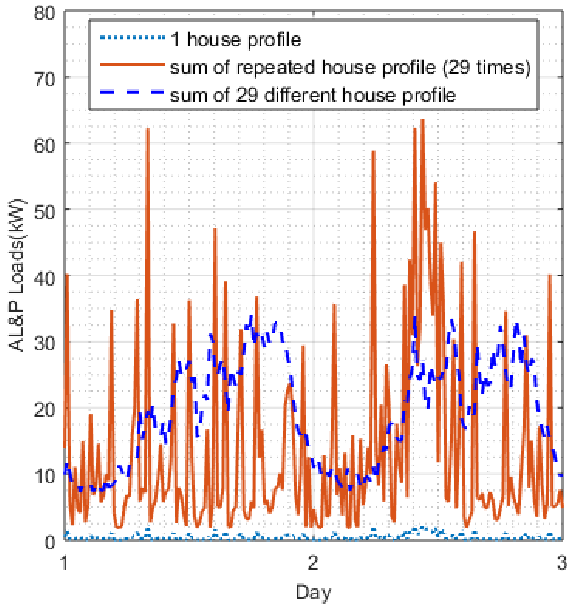

Figure 2 Effect of scaling a single profile vs. using several unique profiles

In Figure 2 there are three profiles spanning two days at 15-min time-steps: 1) the lower-most profile (dotted light blue line) is for a single house, 2) the very erratic profile (solid orange line) is simply the single-house profile multiplied by a factor of 29, 3) the third profile (dotted blue line) is the sum of 29 unique house profiles. It is obvious that the 'repeated' profile results in extreme peaks and valleys and very fast changes in load magnitude, dropping by up to 2000% (~60 kW) in one time-step). In contrast, the sum of 29 different profiles results in a less variable curve, which is representative of the true timestep load curve of a community.

Recently, occupant load data has become available from various sources. Four separate datasets have been obtained including two DHW consumption datasets and two electricity load datasets. This research aims to incorporate these new occupant load profiles into existing residential Archetype building models created by U.S. the Department of Energy. Existing load schedules for these models will be replaced with new, high resolution time-step measured profiles and the buildings will undergo a batch simulation to evaluate the electricity load of a hypothetical tract home community of nine identical homes.

LITERATURE REVIEW

Previous research has focused on energy and greenhouse gas emissions modelling on a community scale. For example, Han et. al. (2015) simulated solar PV in combination with proton exchange membrane fuel cells (PEMFC) for a neighbourhood of 12 south facing Ontario houses. This study was intended to demonstrate the potential to reduce the required backup electricity provided by the electrical grid for a PV-PEMFC coupled system compared to a stand alone solar PV. The technologies were modeled using the ESP-r building simulation software and to represent the residential community electricity load, 12 load profiles developed by Saldanha and Beausoleil-Morrison (2012) were used. The results demonstrated a 82.5% reduction in grid imports and a 24% reduction in required grid backup capacity for the PV+PEMFC coupled system as compared to a stand alone PV system.

Another example of community scale modelling is the Canadian Hybrid Residential Energy Model (CHREM). The CHREM draws from the Canadian Single-Detached and Double/Row Housing Database (CSDDRD), a database of 17,000 single detached, double and row houses representative of the Canadian housing stock. A complete description of the CSDDRD can be found in Swan et. al. (2009). This database is coupled with the ESP-r building simulation tool to estimate aggregate energy consumption for Canadian homes and communities.

To model ALP and DHW loads, the CHREM uses previously developed neural networks model to estimate annual ALP and DHW energy consumption for each house in the CSDDRD. Secondly, a limited set of nine ALP profiles generated by Armstrong et. al. (2009) and three DHW consumption profiles generated by Jordan and Vajen (2001) were used as a base to generate a profile for each home in the CSDDRD. For each home, a profile was selected and adjusted by a 'multiplier' so that the annual consumption of the profile matched the annual estimate for the house. This methodology is described in detail by Swan et. al. (2011). As a result of using only a small number of profiles, they are limited in diversity and result in unrealistic peaks and valleys when conducting time-step demand analysis at a community scale.

PROFILE DESCRIPTION

This section provides a summary of the four separate occupant load datasets that have been obtained and analyzed.

DHW Consumption Measurements

Measured DHW consumption data has been received from two sources. First, a dataset of 1-minute time-step DHW consumption measurements was generatated through the Halifax Regional Municipality's Solar City pilot program. This will be refered to as the *Solar City dataset.* This includes data from 119 houses in Halifax County, Nova Scotia from which 45 annual profiles have been selected. A detailed account of this dataset and profile selection is described by George et al. (2015).

A second dataset includes 1-minute time-step DHW consumption measurements, from the Natural Gas Technologies Center (NGTC). This dataset will be refered to as the *NGTC dataset*. Data was collected from January 2012 to February 2014 in 41 houses across Canada. For 37 houses, data was collected for one year or more and these homes were selected to create annual profiles using the same methods as George et al. (2015). Meta data such as house location (city/province), construction year, house floor area and occupancy where also collected. Of the 37 homes with annual data, 22 are located in Southwestern British Columbia, 4 are located in the British Columbia interior, 5 are located in Regina, Saskatchewan, 3 are located in Southern Ontario and 3 are located in Quebec.

For both the Solar City and NTGC datasets, DHW consumption patterns varied widely between households. However, on average, the Solar City houses consumed less water than NGTC houses. Table 1 shows the daily average statistics for both dataset.

Table 1 Statistics of daily DHW consumption for two datasets

Statistic	Solar City DHW Consumption (L/day)	NGTC DHW Consumption (L/day)
Mean	172	211
Median	159	204
Maximum	615	401
Minimum	21	67

In order to develop a method of allocating a DHW profile to a particular building model, it was important to conduct an evaluation of the factors that influence DHW consumption. Occupancy was found to exhibit the strongest influence over magnitude of consumption while neither the age of the homes nor' size of the home show a strong correlation. This is shown in Figure 3 which plots the average daily consumption and occupancy for each house of the two datasets as well as the average behavior across each dataset represented by the best fit lines.

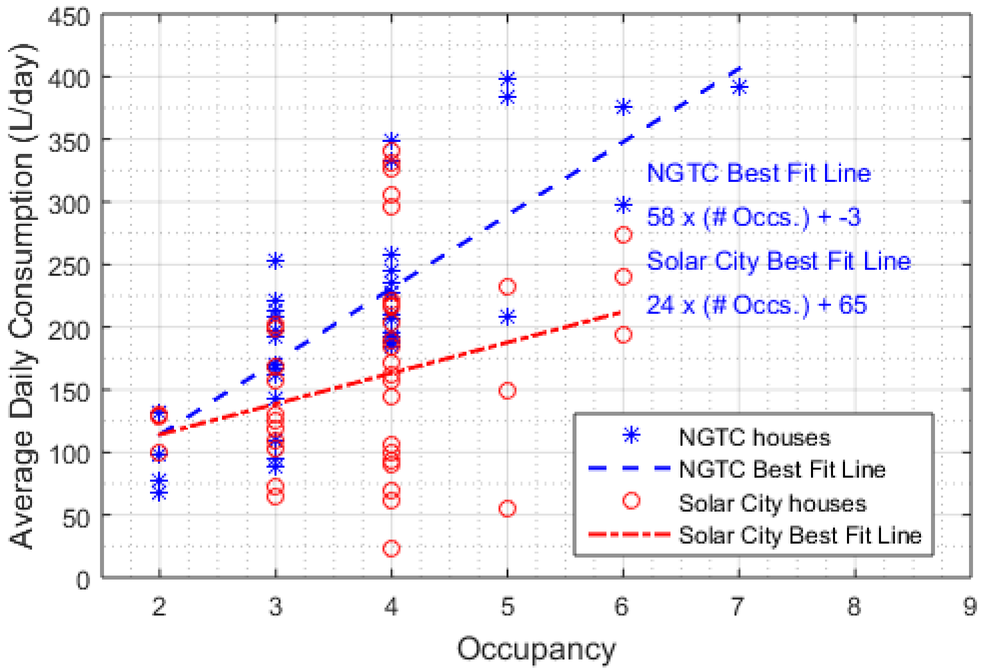

Figure 3 Average daily consumption and occupancy for both sets of DHW annual profiles

From Figure 3, it is obvious that the two datasets both demonstrate a positive linear relationship between occupancy and magnitude of DHW consumption. For this reason, it is suggested that when these profiles are applied in building simulation, a DHW profile is selected for a building model with a corresponding occupancy.

ALP Load Profiles

Two residential electricity load measurement datasets have been obtained for this research. First, a research grade dataset of 1-minute time-step disaggregated electricity load measurements has been obtained from the Sustainable Building Energy Systems research group at Carleton University. This dataset includes annual data from 23 homes located in Ottawa, Ontario, including 22 annual ALP load profiles. A detailed account of this dataset and profile generation is described by Saldanha and Beausoleil-Morrison (2012) and Johnson and Beausoleil-Morrison (2015).

Additionally, 15-minute time-step whole-house electricity load measurements have been provided by Nova Scotia Power Incorporated. This dataset includes measurements from 161 homes throughout Nova Scotia from which 29 annual ALP load profiles have been distinguished. A detailed account of this dataset and ALP profile generation is described by George and Swan (2016). Some of the 29 ALP profiles include up to three years' worth of data so that in total, there are 66 unique annual ALP profiles.

The load characteristics from the Ottawa and Nova Scotia datasets were comparable in magnitude and usage characteristics. Statistics of average daily load are shown in Table 2 and the average hourly load profile for each dataset is shown in Figure 4.

Table 2 Statistics of daily DHW consumption and ALP load for each dataset

Statistic	Nova Scotia Selected ALP (kWh/day)	Ottawa ALP (kWh/day)
Mean	16.3	14.3
Median	16.8	12.6
Maximum	33.6	30.1
Minimum	4.4	5.9

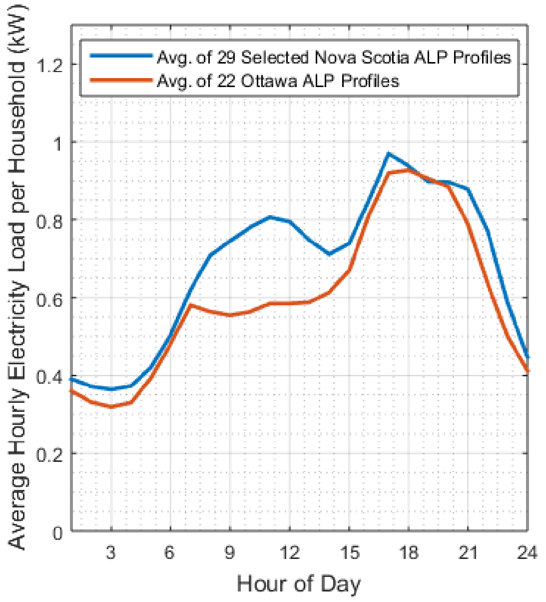

Figure 4 Average hourly ALP load for Nova Scotia and Ottawa datasets

To inform the application of the ALP profiles for building simulation purposes, it is helpful to evaluate the factors of influence such as occupancy, building square footage and major appliances. These types of 'metadata' were available for the Ottawa dataset, but not for the Nova Scotia dataset. Both average and peak loads ALP were evaluated against the factors of influence and the results are shown in Table 3.

Table 3 Correlation of three factors of influence to average and peak ALP loads

Factor of Influence	Mean ALP Load	Peak ALP Load
	Correlation (R^2)	
Age of Home	0.18	0.00
Size of Home	0.11	0.47
Occupancy	0.23	0.01

From Table 3 it is clear that the size of the home exhibits a minor influence on the peak ALP loads, while the age of the home and occupancy have very minor influence on the mean ALP loads. An explanation for this might be that a larger home can generally contain more appliances, more lights and more plug-load devices, and therefore the 'load potential' is higher than that of an average smaller home. Meanwhile, it will be the occupancy behaviour (and to some extent occupancy level) that influences the overall usage of these devices. It should be noted that only 22 homes of the Ottawa dataset are included in this analysis, and therefore these results may not be representative of the larger building stock.

SIMULATION

The load profiles described in the previous section are being incorporated into previously existing EnergyPlus based, building models. These models are called the Residential Prototype Building Models and were developed by the Pacific Northwest National Laboratory (Taylor et. al. 2015) and will henceforth be referred to as the Archetype Models. They are available for download on the Department of Energy website (https://www.energycodes.gov/development/residential/iecc_models).

The Archetype Models were created to estimate energy savings associated with building and energy code changes throughout the United States. First, for several regions throughout the United States a model was created for a representative single-family prototypical house of new construction and operating assumptions. Then, these models are expanded into several variants with four different foundation types (slab, crawlspace, heated basement, unheated basement) and four different heating system types (electric resistance, gas furnace, oil furnace or air-to-air heat pump). As energy code changes are implemented, new models were generated for each location and building type to represent the new energy code construction requirements, so that currently, models exist to align with the 2006, 2009 and 2012 International Energy Conservation Codes (ICC 2012).

The existing ALP and DHW profiles within the Archetype Models consist of repeated 24 hour profiles for individual ALP and DHW end-uses (e.g. interior lighting, clothes washer, misc. plug-loads etc.). These loads profiles have been constructed, drawing from several resources such as NREL (2010) and ICC (2012). For individual end-uses such as refrigerators, sinks, and clothes washers, a separate 24 hr profile has been generated for weekdays, weekends and vacations.

To demonstrate the value of the new ALP and DHW profiles introduced in the previous section, two tract housing developments are simulated by modelling communities of multiple similar homes.

First, two Archetype Models were selected to represent communities of electrically heated homes with heat pump (HP) heating systems and non-electrically heated homes with natural gas (NG) furnaces. Both communities are identical, aside from the heating system types and within each community, each house model is of identical construction with an unheated basement. Portland, Maine was chosen as a location because of its proximity to the Canadian border. These homes were simulated at a 1-minute time-step with a ALP profiles selected from the Ottawa dataset.

Both communities consisted of nine houses, and nine ALP profiles were selected from the Ottawa dataset in order to cover a range of consumption levels (7 to 30 kWh/day on average). (For this paper, the default

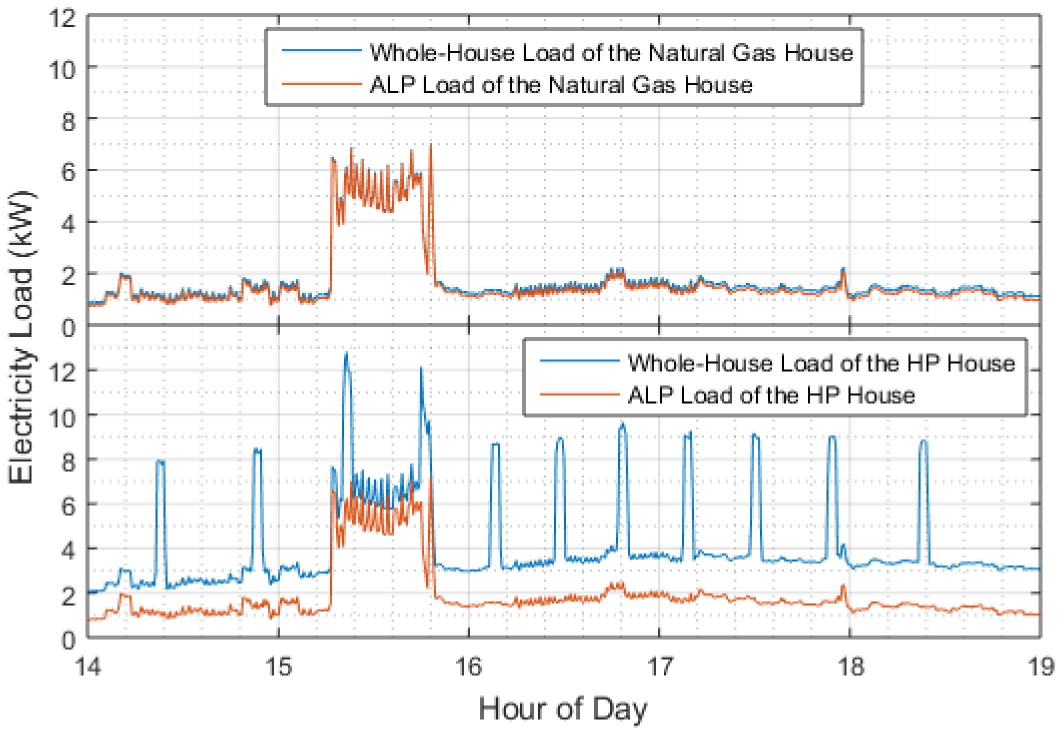

Figure 5 Whole-house and ALP loads for a house with a natural gas furnace and a house with an electric heat pump

hourly DHW profiles from the Archetype Models were used, but will be replaced for future experiments.) The houses were then simulated for an entire year at a 1-minute time-step and the community energy loads were calculated by summing results from the 9 houses of a given heating type.

RESULT ANALYSIS

Several observations emerged from the above simulations. First, the ALP load will influence the electricity consumption of some buildings more than others. For non-electrically heated homes, the majority of electricity consumption is attributed to the ALP loads. This is demonstrated by Figure 5 where the whole-house electricity load and ALP load profiles are shown for a winter day (January 2nd) from 14h to 24h for a home with a gas furnace (upper plot) and a home with an electric heat pump (lower plot). It is clear that electricity consumption of the non-electrically heated home consists almost entirely of the ALP load. Aside from the ALP load, only auxiliary power requirements of the heating system such as fans and pumps would contribute to the electricity load profile of the home. For the home shown in Figure 5, the annual peak whole-house load of 10.5 kW is only 3% larger than the peak ALP load of 10.2 kW. For 8 additional homes, each with a gas furnace and identical construction but with unique ALP profiles, the peak whole-house loads were between 0% and 14% more than the peak ALP load.

From the lower plot in Figure 5, the ALP load accounts for a lesser fraction of the whole-house load. However, the two peaks occurring around 17h are due to the coincidence of the heating loads with large spikes in the ALP load, demonstrating that the ALP load can still account for a significant portion of the peak whole-house load. For the heat pump house, the annual peak whole-house load of 17.1 kW is 65% larger than the peak ALP load of 10.4 kW. For 8 additional homes, each with a heat pump and identical construction but with unique ALP profiles, the peak whole-house loads were between 10% and 75% more than the peak ALP load.

Many characteristics of ALP loads may influence the outcome of a building simulation. In Figure 6, the relationship between the annual peak and mean ALP loads and their relationship to annual peak and mean whole-house loads are explored.

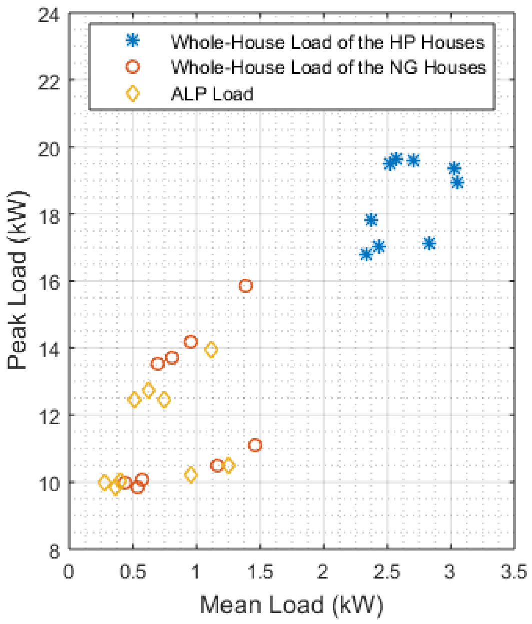

Figure 6 Annual peak whole-house electricity loads vs. annual mean whole-house electricity loads for individual houses

Visual inspection of Figure 6 suggests weekly peak ALP load is independent of mean load in this small sample. For this reason, it is recommended that a single ALP load profile should not be adjusted with a multiplier to represent a home with a different consumption level. If a 'low-mean' ALP profile with a 'high-peak' is multiplied, the peak load of the 'multiplied' profile might become unrealistically large.

Also shown in Figure 6 are the results for the whole-house loads of homes heated with a gas furnace and a heat pump. As expected, for the 'gas furnace' community, the peak vs. mean loads are very close to those of the ALP loads. The 'heat pump' homes have higher peak and mean loads, and there is not a strong relationship between the mean and peak loads.

One way to evaluate the fluctuation of a load is to calculate the 'peak to mean ratio'. This is calculated using the values shown in Figure 6 and the results for all three profiles are shown in Table 4.

Table 4 Range of peak and mean ratios for individual houses and two heating system types

	Peak to Mean Ratios		
	Min	**Max**	**Average**
ALP	8.4	36.7	20.2
Whole-house gas furnace	7.6	22.8	15.3
Whole-house heat pump	6.1	7.8	7.0

As expected, the fluctuation is reduced dramatically when space heating becomes part of the load. For the heat pump house, the peak and mean loads increase by at least a factor of two (Figure 6), but the profile tends to fluctuate less frequently because the space heating loads are more consistent than the ALP loads.

Lastly, this same evaluation is conducted for community loads (sum of the 9 house loads). The peak, mean and peak to mean ratios are shown in Table 5.

Table 5 Peak and mean community loads for two heating system types

	Mean Load (kW)	Peak Load (kW)	Peak/ Mean Ratio
ALP	6.2	31.2	5.0
Gas Furnace	8.0	40.6	5.1
Heat Pump	23.8	142.0	6.0

By using unique ALP loads for each household, the peak to mean ratio is decreased in comparison to the ratios for the individual loads. From the values in Table 5, the reduction occurs for both the communities, but the reduction is much more dramatic for the gas furnace community. Again, this highlights the importance of using a variation of unique profiles for community modelling.

CONCLUSIONS AND FUTURE WORK

This research introduces a database of occupant driven residential load profiles and describes the initial work done to demonstrate their application in community scale demand modelling. A select few of these ALP profiles have been demonstrated in both single household simulations and a community simulation of nine households.

It was demonstrated that the electricity load of single households that do not rely on electricity for space heating and water heating are highly coincident with the ALP profile of the household. Such homes may rely on other common fuel types such as natural gas and home heating oil.

For community modelling, the 'peak to mean load' ratio is reduced from between 6 and 23 to between 5 and 6 when calculated at a community scale as compared to that of an individual house. This reduction is much more pronounced for communities that do not rely on electricity for space heating.

Further research will elaborate on this paper to include all of the available ALP load profiles as well as the DHW load profiles. The effect on the 'peak to mean load ratio' will be explored for a community of at least 50 houses, each with a unique set of ALP and DHW occupant load profiles. Also, the model will be expanded to evaluate the community scale application of an existing building technology such as solar PV.

Once we have demonstrated their effectiveness, we hope that these load profiles will be put to further use by other researchers to evaluate community energy load or to evaluate building technologies for various user-types.

ACKNOWLEDGEMENT

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