New Profiles of Occupancy Driven Appliance, Lighting, Plug Loads and Hot Water Use for Residential Sector Energy Demand Modeling

by

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I dedicate this thesis to my ‘partner-in-crime’, Mary Frances Lynch. She encouraged me to undertake this degree which has led to many good learning experiences and fun relationships.

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Abstract

Energy modeling is used by researchers to estimate aggregate energy consumption and time-step load (power) of buildings. However, researchers often rely on a limited number of occupant load profiles that are repeated for multiple houses to represent communities, resulting in unrealistic load peaks and valleys that do not permit comprehensive demand evaluation. In this thesis, new methods have been developed to generate annual domestic hot water (DHW) and electricity load profiles from measured datasets to address these aggregation issues.

Two measured electricity and two measured DHW datasets were obtained through electrical utility metering programs, academic and industrial research endeavors, and municipal energy savings programs. From these datasets, 82 new annual 1-minute DHW profiles and 62 new annual 15-minute ALP profiles have been generated.

To demonstrate the effect of using a variation of profiles, individual household and community scale building simulations were conducted and both technical and economic applications were demonstrated.

List of Abbreviations and Symbols Used

AEH	all-electrically heated
ALP	appliance, lighting and plug loads
Archetype Models	Residential Prototype Building Models were developed by the Pacific Northwest National Laboratory
ASHRAE	American Society of Heating, Refrigeration and Air Conditioning Engineers
CETC	CANMET Energy Technology Center
CHREM	Canadian Hybrid Residential End-use Energy and GHG Emissions Model
C_p	specific heat
CSDDRD	Canadian Single-Detached and Double/Row Housing Database
DHW	domestic hot water
DST	daylight savings time
EnergyPlus	The EnergyPlus building simulation program
ER	electric resistance
ESP-r	The ESP-r building simulation program
ETS	electric thermal storage
EV	electric vehicle
GHG	greenhouse gas
HOT2000	The HOT2000 energy simulation and design tool
HP	heat pump
HVAC	heating, ventilation and air conditioning
ICC	International Code Council
IDF	EnergyPlus input file
L	litre
LPM	Litres per minute
NEB	National Energy Board
NEH	non-electrically heated
NG	natural gas
NGTC	Natural Gas Technologies Center

NRCan	Natural Resources Canada
NS	Nova Scotia
NSPI	Nova Scotia Power Incorporated
OpenStudio	A collection of software tools to support whole building energy modeling
OTT	Ottawa
PEMFC	proton exchange membrane fuel cells
PPM	pulses per minute
PV	photovoltaic
R	correlation coefficient
R^2	square of correlation coefficient
RETScreen	The RETScreen clean energy management software
Solar City	Halifax Regional Municipality government pilot program
TOD	time-of-day
TOU	time of use
SketchUp	The Trimble SketchUp three dimensional modeling software
TRNSYS	The TRNSYS transient system simulation tool
USA	United States of America
WEL	Web Energy Logger
ρ	density

Acknowledgements

First and foremost, I would like to thank my supervisor Dr. Lukas Swan for the opportunity to undertake this project and for his guidance and enthusiasm throughout. I believe that a work atmosphere is largely influenced by the attitude of a team leader and Dr. Swan, certainly made my experience with RESL an enjoyable one. He is very comfortable in the technical realm and I am amazed at his ability to dream up new research ideas that are relevant in today's world. He has also been a great mentor in the faculties of written and oral communication and his guidance will certainly have a lasting impact on my attitude, my abilities and my confidence level.

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Chapter 1 Introduction

In Canada, energy consumed by households' accounts for 17% of secondary energy use and 14% of greenhouse gas (GHG) emissions (NRCan 2014a). 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 floor space is expected to decline due to improvements in building construction practices (NEB 2013). For both new construction and retrofits, most builders will focus on implementing high performance building technologies.

Time-step load of these technologies can concern a range of stakeholders: (1) homeowners and builders will seek to understand the performance and cost savings of their new technologies while operating within time-of-day pricing schemes; (2) conventional energy providers (e.g. electricity, natural gas) seek to accurately forecast short-term loads so that they can procure sufficient capacity, as well as understand localized distributed generation so that they can install adequate distribution equipment (e.g. polemounted transformers) for net-zero energy communities. 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).

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 and can be used to predict the behavior of high performance technologies. 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

(DHW) consumption and appliance, lighting and plug loads (ALP). Inter-household variation of these loads is significant and is demonstrated by Figure 1.1 which shows the average hourly ALP load for 5 households that will be introduced in Section 3.3.1 of this thesis.

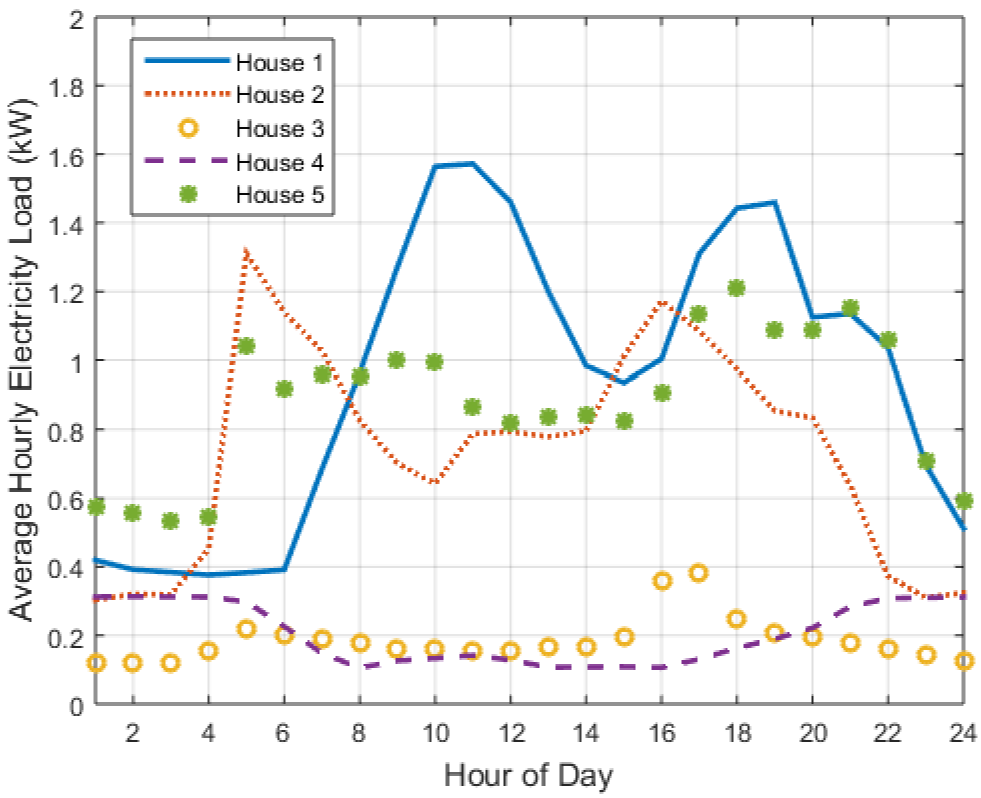

Figure 1.1 Examples of daily variations in household electricity load

Each house in Figure 1.1 demonstrates unique characteristics. Notably, they do not all 'peak' in load simultaneously. On average, one household may be characterized as a 'night-time' user of electricity or DHW (e.g. House 4), or 'diurnal' user (e.g. House 1 and House 2). 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.

The use of a variety of profiles is also necessary when using simulation to evaluate such technologies in community scale applications. 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 1.2 with occupant load profiles that will be introduced in Section 3.3.1 of this thesis.

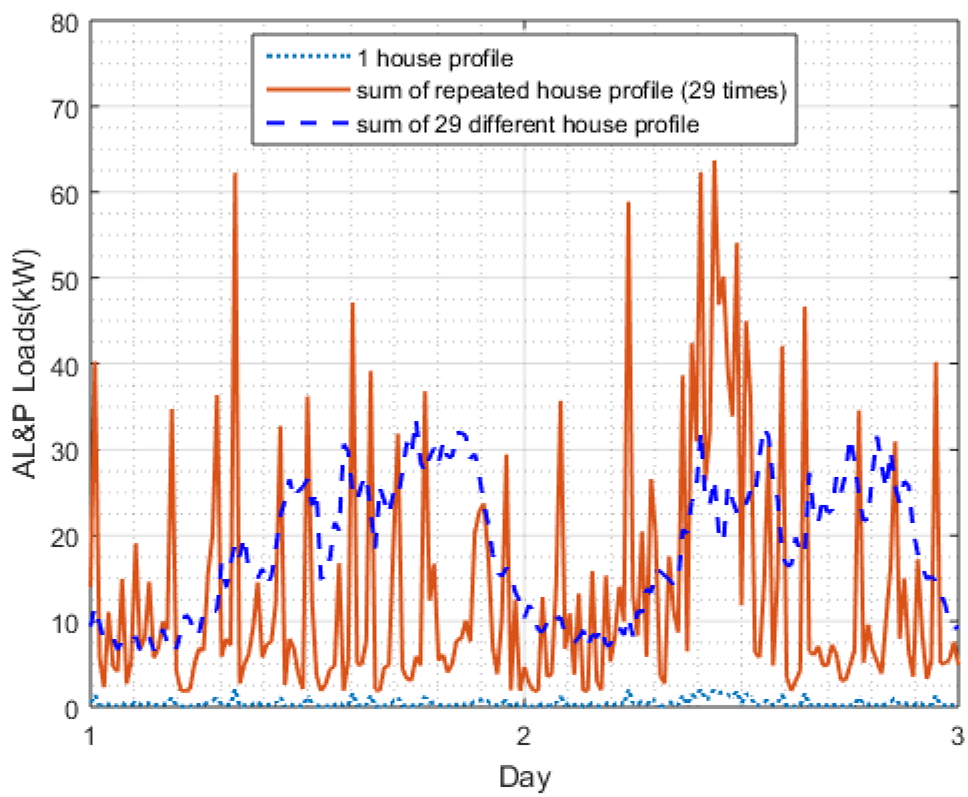

Figure 1.2 Effect of scaling a single profile vs. using several unique profiles

In Figure 1.2 there are three profiles spanning two days at 15-minute 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 time-step load curve of a community.

1.1 Background

With respect to DHW, studies which examine residential consumption characteristics in Canada and abroad date back several decades. Perlman and Mills (1985) collected DHW consumption data in the 1980's and developed a 24-hour profile at 1-hour time-steps. These values are still the basis for the Service Water Heating: Hot Water Requirements and Storage Equipment Sizing section of the 2011 ASHRAE Handbook: HVAC Applications (ASHRAE 2011). More recent Canadian studies have emerged as well but have either relied on DHW heating energy consumption to estimate DHW consumption (Swan et al. 2011; Evarts and Swan 2013) or on measured DHW consumption data with measurement periods of less than 1-year (Thomas et al. 2011; Edwards and Beausoleil-Morrison 2015). In Chapter 2 of this thesis, these studies will provide a basis to compare with new DHW consumption data.

Several studies have also analyzed residential electricity consumption measurements over the past decade. There are two studies in the Canadian context that are of major significance to this research as they have generated annual ALP load profiles at high temporal resolution (1-minute time-steps). To accomplish this, Saldanha and Beausoleil-Morrison (2012) and Johnson and Beausoleil-Morrison (2016) deployed research grade data acquisition systems in 23 houses in Ottawa, Ontario. These datasets have been obtained and utilized in Chapter 3, Chapter 4, and Chapter 5 of this thesis.

As an alternative to the collection of measured data, researchers have generated synthetic electricity load profiles. A recent example in the Canadian context are the profiles generated for the IEA Energy Conservation in Buildings and Community Systems Programme's Annex 42 (Knight et al. 2007). One of the objectives included the characterisation of ALP and DHW usage patterns and so nine 5-minute time-step ALP profiles were generated by Armstrong et al. (2009) and the 1-minute time-step DHW consumption profiles which had been previously generated by Jordan and Vajen (2001a) were calibrated to Canadian data. These profiles are used in Chapter 4 of this research to compare and validate the need for new measured occupant load data.

1.2 Objective and Outline

The primary objective of this research is to obtain recently measured occupant load data from which to generate new occupant load profiles for building simulation tools. These profiles will help address aggregation issues in residential community simulation scenarios and provide a range of high temporal resolution occupant behavior characteristics for technology simulations. While it is recognized that occupant behavior will change over time, there will be an onset of new measured data through electrical utility 'smart metering' programs, academic and industrial research endeavors, and municipal energy savings programs. This research establishes methodology for analyzing new datasets as they become available and making the appropriate data corrections to produce continuous annual profiles.

Four separate datasets have been obtained for our research project:

- two multi-year datasets including 1-minute time-step DHW consumption measurements from 41 and 119 houses
- one three-year dataset including 15-minute time-step whole-house electricity load measurements from 161 homes
- one annual dataset including 1-minute time-step sub-metered electricity load measurements from 23 homes

This research project analyzes these datasets, forms new annual occupant driven load profiles and demonstrates their impact in building simulations. The thesis is divided into four main sections:

Chapter 2 analyzes the DHW consumption datasets and constructs 82 annual 1-minute time-step DHW profiles. This section also presents a new method to calibrate and interpret water flow rate measurements made on 1-minute time-steps.

Chapter 3 contrasts two electricity load datasets to develop a new method of identifying ALP profiles. A total of 62 new 15-minute time-step annual ALP profiles are identified from 29 houses.

Chapter 4 implements the new profiles using the building simulation tool EnergyPlus and compares results with those generated using existing occupant load profiles. Two applications are demonstrated: a technical evaluation of tankless water heaters and an economic evaluation of an alternative electricity tariff.

Chapter 5 demonstrates the application of the new occupant load profiles at a community scale. A technical application is demonstrated: the sizing of pole mounted electricity transformers for various community configurations.

Chapter 2 Measured Domestic Hot Water Consumption Profiles of Canadian Homes

This Chapter was previously published as:

George, D., Pearre, N. S., & Swan, L. G. (2015). High resolution measured domestic hot water consumption of Canadian homes. Energy and Buildings, 109, 304-315. doi: http://dx.doi.org/10.1016/j.enbuild.2015.09.067

It has been included in this thesis under the terms of the license agreement with Elsevier. The copyright license agreement is provided in Appendix F.

Dane George is the principal researcher and author of the article. He conducted the research as part of his MASc. Thus, while he received supervision and guidance from his supervisor Dr. Swan and advisor Dr. Pearre, he carried out the work, wrote the published article, communicated with the editor of the journal, and carried out the necessary revisions before publication. The article has been edited and expanded upon to include the analysis of an additional dataset and to be integrated within this thesis.

2.1 Introduction

Energy consumed for DHW heating is significant. In 2011 the heating of DHW accounted for 20% of residential end-use energy consumption in Canada (NRCan 2014a). Numerous technologies have, and are, being developed to reduce DHW consumption and make the conversion of energy more efficient. The creation of energy policy to support implementation of such technologies relies on accurate modeling and simulation of the performance of such systems. It is critical that such simulation captures the high temporal resolution effects of water draws to insure high fidelity representation of such systems.

At present, technologies such as residential solar DHW systems, solar combi-systems, combined heat and power systems, ‘net-zero’ energy building design and ‘smart-grid’ applications can be modeled using two classes of simulator packages. Simplified software such as RETScreen and HOT2000 accepts an average daily DHW consumption estimate (CETC 2016b; CETC 2016a), while more advanced simulation software such as EnergyPlus, TRNSYS and ESP-r require occupant load profiles at more frequent time-steps to generate high resolution energy end-use estimates. Temporal consumption patterns and the magnitude of consumption can impact not only the accuracy of these models but also the performance of DHW systems (Jordan and Vajen 2001b; Edwards and Beausoleil-Morrison 2015). Therefore, it is important to use realistic profiles, preferably from measured data, for simulations.

Measuring DHW consumption at high temporal resolution requires a flow meter and a data acquisition system which are relatively expensive to purchase and install. Historically, measured data at time-steps under 5 minutes have been unavailable and researchers have instead relied upon repeated daily profiles (e.g. Fung and Gill 2011), synthetic profiles (e.g. Swan et al. 2013), or have utilized profiles based on limited or historic datasets (e.g. Edwards and Beausoleil-Morrison 2015).

Two new measured DHW consumption datasets are presented in this section:

- “Solar City” in Halifax, Nova Scotia is a municipal government pilot program which provides financing, sourcing and installation of solar DHW systems to homeowners in Halifax Regional Municipality (NRCan 2014b). At homeowners’ discretion, the installation includes a data monitoring system which measures flow rate and fluid temperatures at 1-minute time-steps. By the end of July 2015, over one-hundred systems that include data monitoring had been installed throughout the Municipality. In addition, each monitoring system is linked to occupancy information and other relevant meta-data gathered through a survey of participants.

- The Natural Gas Technologies Centre (NGTC) is a non-profit organization promoting technological development and advancing the efficient use of natural gas and renewable energy. For research purposes, the NGTC monitored the energy use of natural gas water heaters in homes across Canada from 2012 to 2014. Standardized energy monitoring systems were deployed which measured flow rates and fluid temperatures at 1-minute time-steps. Furthermore, relevant home information was collected, such as location and occupancy.

The Solar City program and NGTC's research initiative have made available measured data of DHW flow measurements for complete-year and multi-year periods at high temporal resolution (1-minute time-steps).

This Chapter achieves the following: (1) it introduces two new datasets, (2) it describes the data acquisition systems and participant characteristics, (3) it examines DHW consumption characteristics such as mean daily DHW consumption, occupancy influence, day/time-of-use influences, and (4) it generates and describes new DHW profiles for incorporation with building performance simulator packages.

2.2 Background and Literature Review

Several studies of DHW consumption have been in conducted in Canada and the USA. Beginning in 1981, Perlman and Mills (1985) collected DHW flow measurements at 15-minute time-steps in 59 homes throughout Ontario and examined household DHW consumption based on a variety of occupancy variables. Daily, monthly, and seasonal (winter/summer) average usage patterns were analyzed and representative daily profiles were generated for the entire population, and for what was deemed to be a 'typical' family. In order to aid with DHW system sizing, 'probabilistic' profiles were developed to represent DHW requirements of 95% of the sample population.

Becker and Stogshill (1990) compiled a database from nine studies totalling more than 30 million DHW consumption measurements at 15-minute time-steps for both apartment buildings and homes throughout Canada and the USA. The Perlman and Mills (1985) study is included in this database and although many of the same factors of influence were investigated, it was possible to expand on these factors due to the breadth of data. It was found that location also had an influence on DHW consumption, which is likely due to differences in outdoor temperatures.

Over the past three decades, several confounding influences including technology, behavior, and demographics may also have changed DHW consumption. For example, faucet and showerhead flow rate standards have decreased consumption. Secondly, 'low-flow' faucets are being installed through many energy and water conservation programs (e.g. Efficiency Nova Scotia 2015). Thirdly, the frequency of ownership of household appliances such as dishwashers and clothes washing machines has increased. Additionally, attitudes may have changed; a large proportion of Perlman and Mills (1985) survey participants 'considered automatic dishwashing as only an occasional alternative to manual dishwashing'. Finally, Canadian demographics have also changed; the average number of persons per private household in Canada has decreased from 2.8 in 1986 to 2.5 in 2011 (Statistics Canada 2013a).

Thomas et al. (2011) conducted a study of 74 households in Ontario aimed to evaluate the daily consumption profiles used in current water heater performance test standards. Measurements were taken for two to three weeks at each house at very high-resolution time-steps of 2 to 4 seconds. They found that average daily DHW consumption was lower than current standards developed from earlier studies.

A recent study by Edwards and Beausoleil-Morrison (2015) included measured DHW consumption data from 73 households in Quebec at a 5-minute time-step. They selected twelve annual profiles to represent four aggregate consumption levels at three temporal demand patterns for those who consumed primarily: (i) in the mornings, (ii) in the evenings or (iii) evenly throughout the day. These profiles were then incorporated into the TRNSYS simulation program to analyze the performance of a typical solar DHW heating system and use of auxiliary heat. For morning users, the auxiliary heater would operate primarily during the day, while for evening users, the auxiliary heater would function primarily overnight, a result more appealing to those with time-of-use electricity rates.

Researchers have also estimated average daily hot water consumption based on energy consumption. Evarts and Swan (2013) estimated average daily DHW consumption based on a sample of homes in the Solar City program. A survey of each home gathered occupancy, water source, water heater type, energy use and energy costs. Average consumption was estimated from fuel oil consumption for occupancies of 1 to 6 people. Since the sample set of homes in this study were initial applicants to the Solar City program, it provides an excellent opportunity to compare the results of this method with the findings of the current study of measured data.

Other research efforts have generated synthetic profiles, where probabilities are assigned to individual end uses such as dishwashing and clothes washing. Jordan and Vajen (2001a) used this approach to create consumption profiles at various time steps and load magnitude based on data gathered in Germany and Switzerland (Knight et al. 2007). Hendron and Burch (2007) used a similar method to generate profiles based on data collected by the American Water Works Association. A drawback of synthetic profiles is the inability to capture the true temporal variability in consumption patterns, as they rely on engineering judgement and expectation.

2.3 Data Source: Halifax Regional Municipality 'Solar City' dataset

All of the Solar City data are the result of acquisition systems being installed with solar DHW heating systems on homes in the Halifax Regional Municipality. To July 2015, 250 data collection systems had been installed; however, data from 77 systems using an earlier version of the control software were not considered. Of the remaining systems, many were installed during the spring and summer of 2015. Only data from systems installed prior to November 2014 were considered to ensure sufficient data for each site. This study includes data from May 2014 to July 2015 for a total of 119 houses. The data collection systems progressively came online with new system installations, with Figure 2.1 illustrating system availability. Note that for several systems, connection failures occurred throughout the timeline, explaining the variable system availability beginning in November 2015.

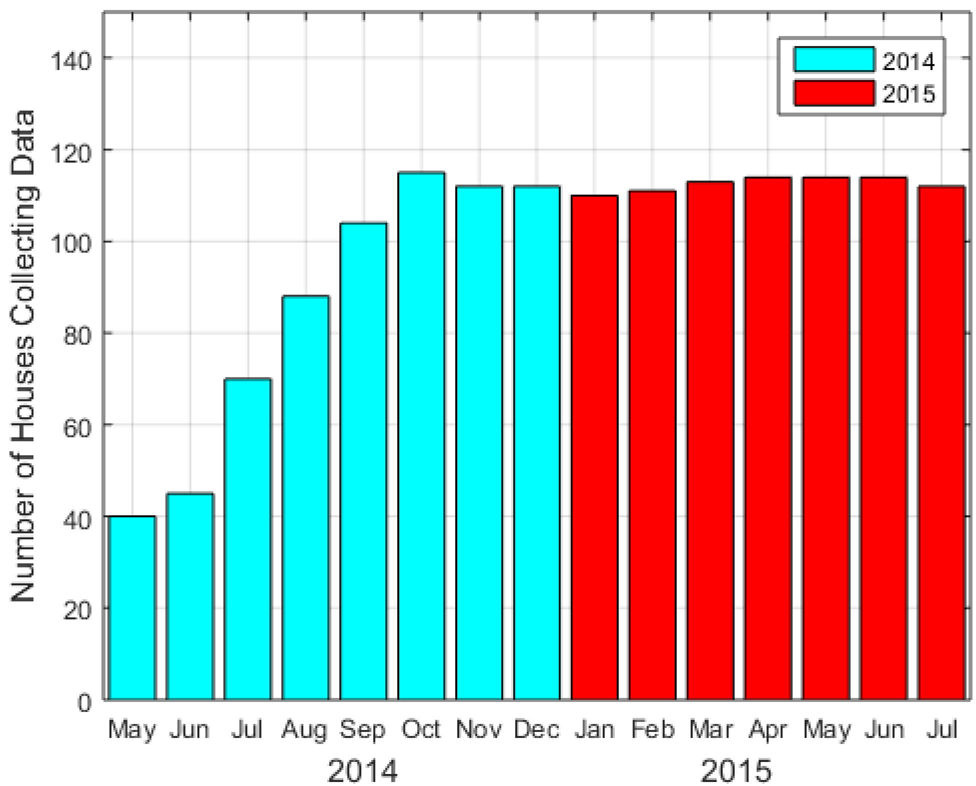

Figure 2.1 Number of active data acquisition systems through time

Occupancy data was collected by a household survey during initial consultations. Of those, 77 homes had detailed occupancy categorized by class with results presented in Table 2.1. The defining ages of each class were not given. Only a total occupancy with no detailed categorization was recorded for 26 additional homes, thus occupancy records were deemed valid for a total of 103 houses. Of these houses, 45 had at least one full year of data collected.

Table 2.1 Household occupancy by age class

Total number of homes	119		Number of homes with no occupancy data		16	
Occupants	Number of Homes	Number of homes with occupancy breakdown	Average number of occupancy type per home			
			Adults	Seniors	Teenagers	Children
1	1	1	1	0	0	0
2	14	11	1.91	0.09	-	-
3	26	20	2.30	0.05	0.10	0.55
4	44	34	2.56	0.03	0.50	0.91
5	10	7	3.00	-	0.29	1.71
6	4	3	2.67	-	0.67	2.67
7	0	0	-	-	-	-
8	0	0	-	-	-	-
9	2	0	-	-	-	-
10	2	1	10.00	-	-	-
Total	103	77				
Average occupancy across all homes	3.83	3.65	2.51	0.04	0.30	0.81

2.3.1 Data Representativeness

There are three concerns about using the Solar City data to represent the DHW use patterns of a wider region.

First, all measurements were conducted for houses with solar DHW heating systems. There is a risk that occupant behavior adjusts to better utilize the system (e.g. showering in the morning versus the evening). Alternatively, since marginal cost of DHW is lower than for an equivalent system without the solar component, an occupant of a solar-equipped house might consume more DHW. Additionally, since a larger store of heated water is available to some occupants with the additional solar 'pre-heated' tank, occupants may tend towards prolonged draws. Perlman and Mills (1985) encountered the same problem and concluded that consumers have well-established DHW use habits which will likely remain unchanged regardless of the water heater system type.

Second, during the on-site survey, low-flow faucets and showerheads were installed in 20% to 50% of the homes, depending on fixture type. These devices could significantly reduce DHW consumption, and the analysis of the retrofits suggested that they reduced flow rates by between 20% and 50% per home (Adye et al. 2014). After the installations, the frequency of low-flow devices within the Solar City sample may not represent the larger population. However, the use of low-flow devices has become more widespread nationwide due to government and utility sponsored energy efficiency programs, evidenced by the large proportion of houses in the Solar City sample that were already equipped with such devices (Adye et al. 2014).

Finally, participants in the Solar City program are a self-selecting sample, and so may not be representative of the population as a whole. For instance, the average household occupancy in the study is 3.8 versus the national average of 2.5 and the Nova Scotia average of 2.3 (Statistics Canada 2013a). It is likely that the Solar City program attracted larger than average households since small households with lower DHW consumption may not have been interested in investing in a solar heating system. For this reason, this study puts emphasis on consumption levels specific to occupancy. The uncertainly associated with a self-selecting sample not necessarily being representative of the broader population remains.

2.3.2 Data Acquisition Systems

Data acquisition systems were supplied and installed by the original equipment manufacturer as part of the Solar City program. A typical system schematic is shown in Figure 2.2. Note that the auxiliary tank (far right) is a pre-existing component in the homes and that some homes may have an tankless DHW heater instead (powered by either electricity, natural gas, or heating oil).

The data acquisition system is a Web Energy Logger (WEL), which primarily measures digital signals via a communication protocol or pulse counts (Malone and Malone 2013). The WEL records data on a 1-minute interval and posts this information in real-time to a server. All data are recorded into monthly log files.

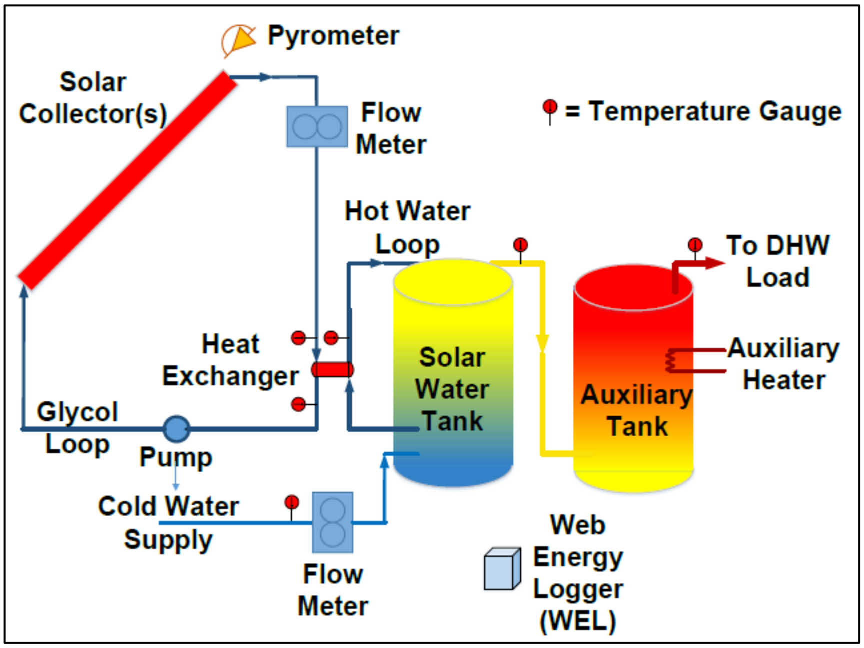

Figure 2.2 Schematic of a typical Solar City hot water heating system with data acquisition

The flow meters used in this study are impeller type USC-HS43TB Big Hall Flow Sensor (Ultisolar Group 2010). These are a consumer grade product, valid for a range of 1 to 30 litres per minute (LPM), but are supplied without accuracy information. These sensors produce digital pulses when subject to flow. The WEL uses a counter to accumulate these pulses over a 1-minute period and then timestamps this value.

2.3.3 Data Calibration and Processing

The water flow measurement presented difficulties due to changing impeller response as a function of flow rate, measurements outside the nominal range of the flow meter, and the presence of sub-minute draws in 1-minute time-step data.

First, the conversion of the flow meter pulses per minute (*PPM*) to volumetric DHW consumption rate in litres per minute (*LPM*) was found to be non-constant, decreasing from infinite values at low *PPM*, to values as low as 0.0021 LPM at high flowrates. Laboratory tests were conducted on two flow meters sourced from the Solar City project to establish the relationship of litres per pulse (*LPP*) to *PPM*. Sensors were placed in series and water was run at a constant flow rate (1.9 to 15.0 LPM) for a period of time (90 to 210 seconds). Then, the mass of water accumulated was measured to 1 in 100 parts with a laboratory scale. A best-fit calibration curve relating *LPP* to *PPM* is given as Equation 1. The two sensors gave consistent and repeatable results with differences within ±2% from the calibration curve. A conservative assumption of ±5% accuracy for values of *LPP* is suggested. To convert measured *PPM* from the flow meter into *LPM*, the calibration *LPP* is determined from *PPM* using Equation 1, and then is used as a conversion coefficient in Equation 2.

$$LPP\ \left(\frac{\mathrm{L}}{\mathrm{pulse}}\right) = \ 0.002\left(\frac{\mathrm{L}}{\mathrm{pulse}}\right) + \frac{0.75\left(\frac{\mathrm{L}}{\mathrm{minute}}\right)}{PPM\left(\frac{\mathrm{pulses}}{\mathrm{minute}}\right)} \tag{1}$$

$$LPM = \ LPP_{PPM} \times PPM \tag{2}$$

Second, because the DHW was not necessarily flowing consistently throughout an entire sampled minute, the averaging effect of the sampling rate could result in the *LPP* conversion coefficient of Equation 1 over-representing the draw. As an example, briefly rinsing a cup at 5 LPM for 6 seconds would appear as 0.5 LPM at the timestamp, and the non-linearity of Equation 1 would overstate the calibration *LPP*. To address this, measurements were categorized into four types for determining the applicable *LPP* calibration coefficient. An example is shown in Figure 2.3 and the treatment of each type of value is explained below. The logic is outlined in the flowchart of Figure 2.4.

- A *single value* is where zero DHW flow occurred in the preceding and following minute. In this case, the flow is assumed to be a sub-minute draw. Unless a higher flow was recorded, the *LPP* calibration coefficient is evaluated at the dataset mode[1] *PPM* of 1532 (3.79 LPM).

- *Double values* are where zero DHW flow occurs immediately before and after a pair of non-zero measurements. This is likely a less-than 2-minute continuous draw spread across two datapoints. As such, the *LPP* calibration coefficient in Equation 1 is evaluated for the largest of (i) the first value in the pair, (ii) the second value in the pair, or (iii) the modal value of 1532 *PPM*.

- A *non-edge value* is where non-zero DHW flow occurred in both the preceding and following minutes. This likely represents legitimate continuous flow throughout the minute. However, at low *PPM* of 375 (1.5 LPM) or less, is assumed to be an intermittent draw, and in this case, the *LPP* calibration coefficient is evaluated at the dataset mode *PPM*.

- An *edge value* is found at either the beginning or end of a draw of three or more minutes' duration. This is likely a sub-minute draw at the same flow rate as the adjacent non-edge value. As such, the *LPP* is evaluated for the larger of either the edge or adjacent non-edge *PPM*, with a two stage evaluation to be consistent with non-edge value logic. Otherwise, intermittent flow is assumed and the *LPP* calibration coefficient is evaluated at the mode *PPM*.

[1] An analysis was conducted to determine a mode *PPM* across the dataset. The distributions of *PPM* values for each house generally had two predominant peaks: a low value peak presumably caused by the time-step averaging effect of sub-minute draws, and a higher peak at 1532 (house-weighted) which is assumed to represent the most common faucet flow rate.

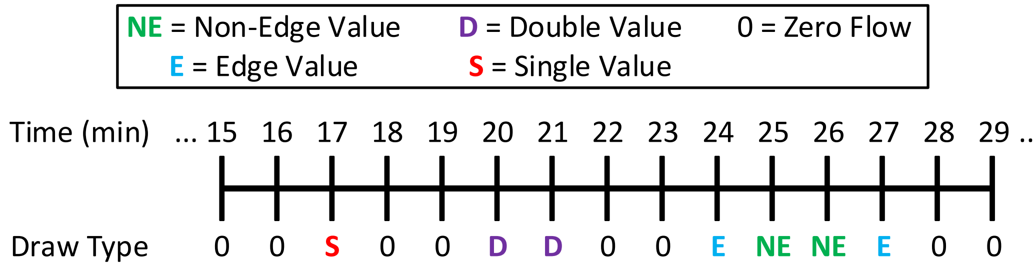

Figure 2.3 Example of DHW Consumption Measurement Categorization

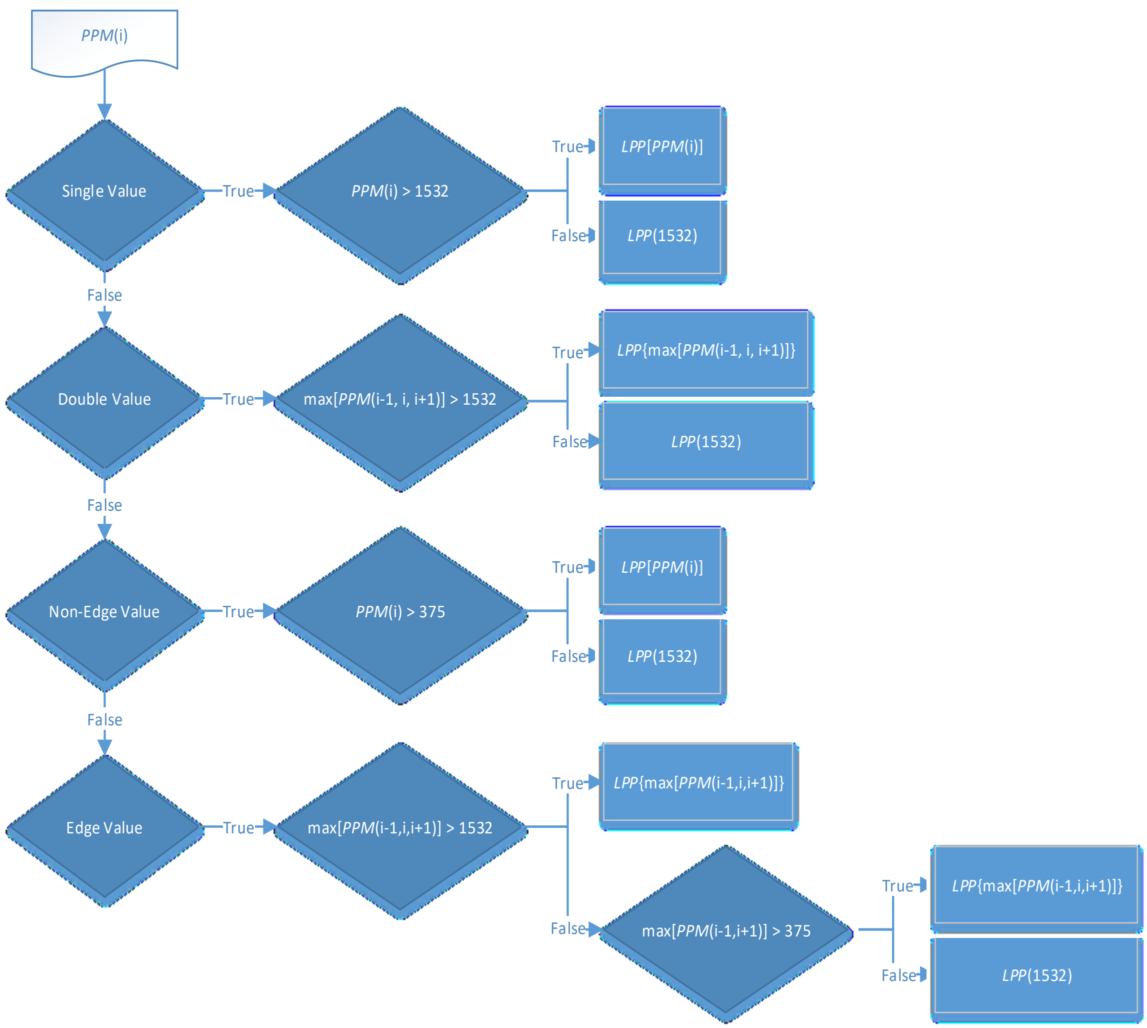

Figure 2.4 Flowchart to determine the flow meter LPP calibration coefficient

To calibrate and verify this method, water consumption measurements were taken at 1-second intervals in a 4-occupant household and the results were compared to measurements taken at 1-minute intervals. To accomplish this, a Campbell Scientific CR1000 datalogger was installed in conjunction with a WEL datalogger and the pulse counts from two flowmeters measuring DHW and cold water supply were recorded by the CR1000 datalogger every second and by the WEL every minute. Data was collected over sixteen days and over this time interval, the pulse count measurement error between the two sensors was within 0.03%.

At a 1-second time-step, flow was assumed to be consistent during the entire 1-second duration of the measurement interval and therefore Equations 1 and 2 could be applied directly to obtain a flow rate for a given interval. These results were used to calibrate the flowchart of Figure 2.4. The flowchart logic was applied to the 1-minute time-step data from the WEL measurements and a range of values for the *low PPM* were evaluated. A value of 375 found to produce very close aggregate DHW consumption between the 1-second and 1-minute time-step measurements, with a difference of 1.00% for the cold water supply (10106 L of water consumed over 16 nine days) and -1.24% for the DHW (4223 L of water consumed over 16 days). The close agreement between the results validates the method presented in the flowchart of Figure 2.4. It should be noted however that while the method produces excellent results over an aggregate period, for a particular minute, the difference between the 1-second and 1-minute time-step measurements varies more significantly. To demonstrate this, a comparison of the two types of measurements over a half hour time-period is shown in Figure 2.5. However, while the individual DHW consumption measurements may not represent reality, the resulting profiles well represent aggregate consumption and temporal variability.

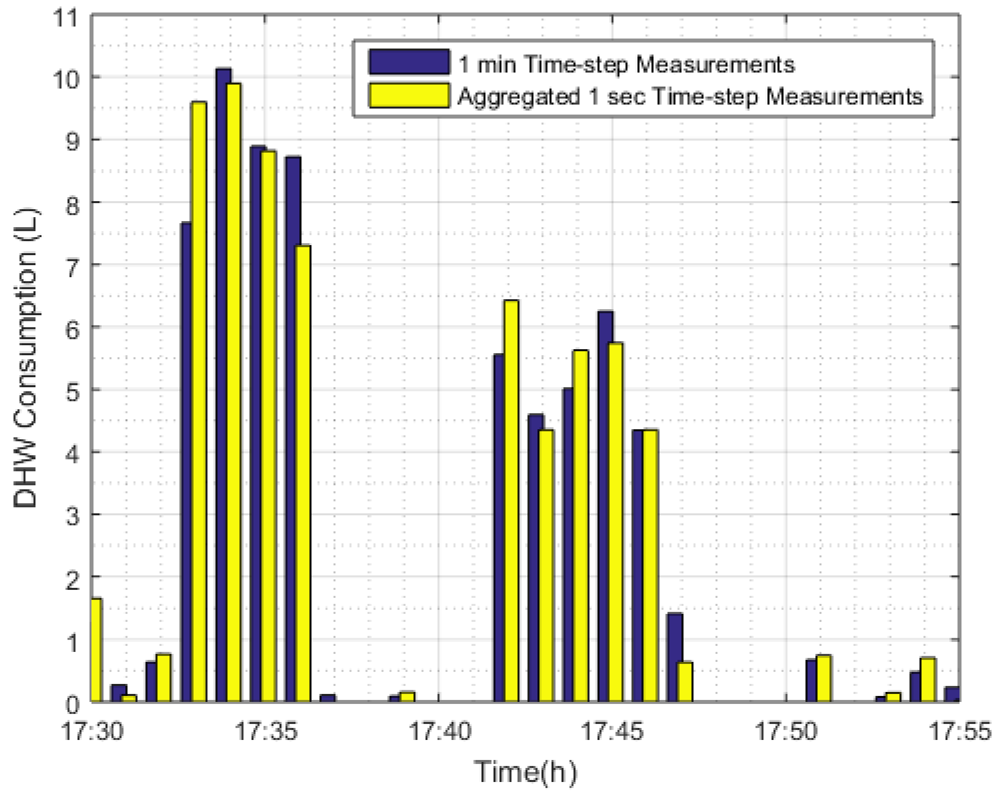

Figure 2.5 Example of 1 second time-step flow measurements and 1-minute time-step measurements

A third source of measurement error relates to readings outside a normal and practical range for household DHW water consumption. Readings greater than 30 LPM are uncommon (0.001% of readings) and have been excluded. Low-value readings may occur for a variety of reasons. Short draws lasting only seconds may be valid, such as rinsing a cup in a sink. However, investigation of the data showed continuous low-value draws (e.g. <0.05 LPM) occurring throughout the night in several houses, and sporadically in other houses. While in some cases this may be a leaky faucet or other fixture, it is likely signal noise, or may be attributed to changing water pressure. Thomas et al. (2011) noted an excess of single pulse DHW draws in 1-second data, and attributed them to water pressure changes and/or convection currents in the water pipes, triggering a pulse. This effect is exacerbated by the flow sensor design, which does not differentiate between ‘forward’ and ‘backward’ flows, but simply sends a pulse when the impeller turns. Values less than 0.05 LPM were excluded, which decreased average household DHW consumption by 4.6%, some of which may-in-fact have actually been consumed.

2.4 Data Source: Natural Gas Technologies Center

This DHW consumption data was collected by the Natural Gas Technologies Center (NGTC) between January 11, 2012 and February 18, 2014 in 41 homes across Canada. For 37 homes, data was collected for one year or more. Meta data such as house location (city/province), year of construction, house floor area and occupancy were also collected.

Of the 37 homes with one year of data, 26 are located throughout British Columbia, 5 are located in Regina, Saskatchewan, 3 are located in southern Ontario and 3 are located throughout Quebec. The homes were constructed between 1875 to 2006 with an average of 1971. The house floor area ranges from 92.3 m^2 (1036 ft^2) to 390.2 m^2 (4200 ft^2) with an average of 217.1 m^2 (2337 ft^2). Neither age or size of the homes show a strong correlation to the magnitude of DHW consumption (R^2 values of 0.216 and 0.200 respectively).

Occupancy ranged from 1 to 7 total occupants with an average of 2.5 adults and 1.1 children per home. Adults are classified as any person 18 years of age or older while children are classified as anyone under 18 years of age.

2.4.1 Data Quality Challenges

Prior to receiving the data from NGTC, it had been adjusted incorrectly for daylight savings time (DST). For the provinces where DST is not observed, the data had been adjusted to show a gap of one hour at the spring time change. However, this occurred only at the 2012 time change and did not occur for the 2013 time change. For provinces where daylight savings is observed, there had been no adjustment.

The contact at NGTC explained that the data was retrieved onto laptops from an online portal called Hobolink (Onset Computer Corporation n.d.). An inquiry to NGTC and to the HoboLink customer support center revealed no solution to the problem but it was suggested that when data was downloaded from the Hobolink portal, a DST adjustment may or may not be implemented depending on the specific time and date settings of the receiving computer. Since NGTC is based in Quebec, it was assumed that all computers were also based in Quebec.

Another issue was also identified: because some of the data has been downloaded in a different province from the data acquisition system (and therefore a different time zone), the some of the data timestamps appeared to be offset by multiple hours. For example, the average morning peak of the British Columbia profiles occurred late in the morning (10h, on average) as compared with the Solar City dataset, which peaked between 7h and 8h. For the Saskatchewan, Ontario and Quebec profiles the average morning peak occurred at 8 am. An example of this is shown in Figure 2.6.

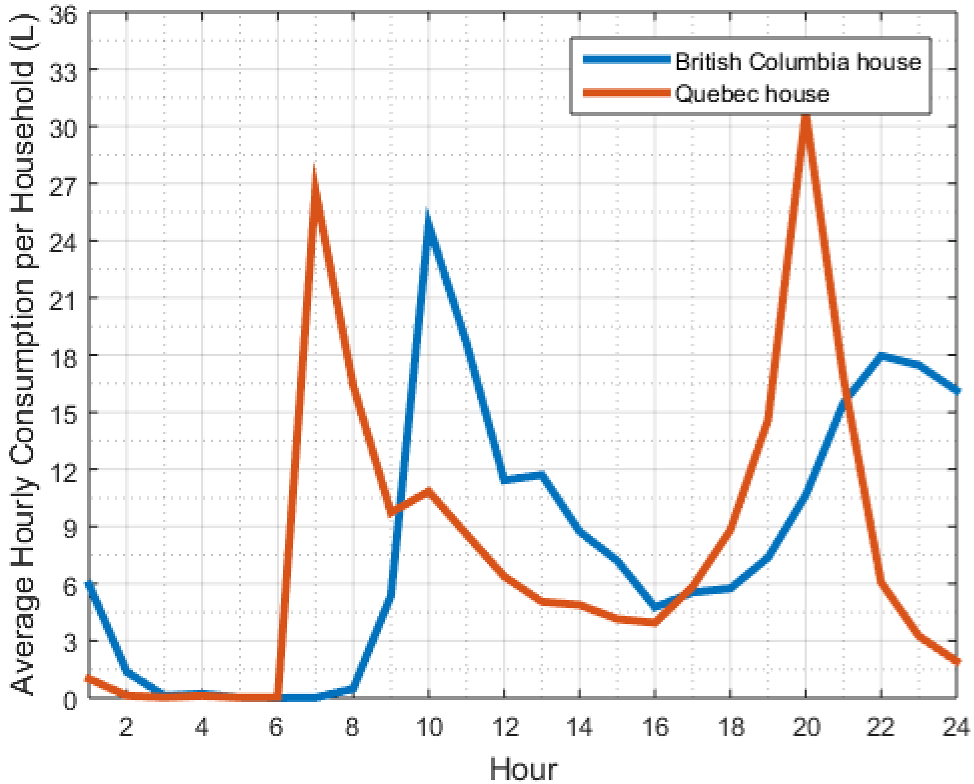

Figure 2.6 **Example average hourly profile of a home in Quebec and a home in British Columbia**

A solution to these problems was established numerically using the following steps:

1) Each profile was adjusted to account for DST. The pre and post adjustment profiles will be referred to as 'DST unadjusted' and 'DST adjusted'.

2) For each house, an average weekday hourly profile was generated for the six weeks preceding a time change ('pre-time change') and the six weeks following a time change (post-time change). This was done for both the DST adjusted and DST unadjusted profiles.

3) The correlation coefficient between the 'pre-time change' and 'post-time change' average weekday hourly profiles was calculated for both the DST adjusted and DST unadjusted profiles and the two correlation coefficients were compared. The DST

adjustment was deemed necessary if the correlation coefficient increased due to the DST adjustment.

4) A ‘time-zone’ adjustment was applied to each profile based on the time difference between the house location and Quebec. British Columbian profiles are shifted three hours back in time and Saskatchewan profiles are shifted one hour back in time. Ontario and Quebec profiles were not adjusted for time-zone error.

The method is confirmed visually by plotting the hourly average DHW consumption between the 4h and 15h for six weeks preceding and following the time-change for both the ‘DST adjusted’ and ‘unadjusted’ datasets. An example is shown for one house in Figure 2.7 for the time change occurring on November 4, 2012 (week 44).

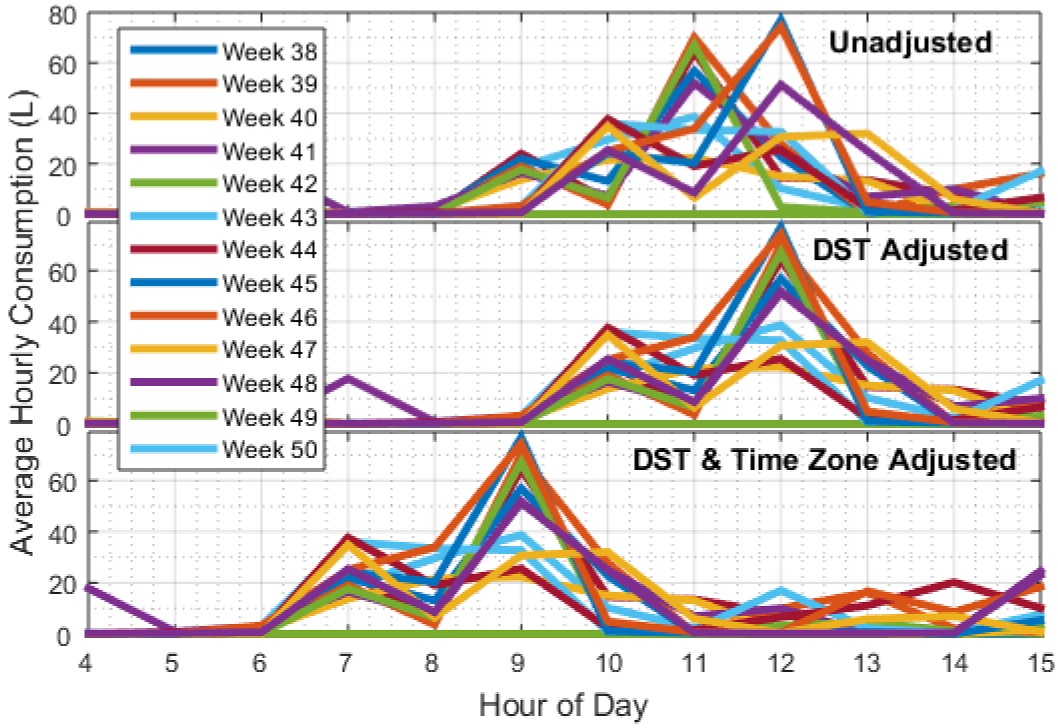

Figure 2.7 DST Unadjusted, DST adjusted and DST/Time Zone Adjusted time-step hourly average DHW consumption profiles for 13 separate weeks for 1 house in British Columbia (time change occurs on week 44)

There is an obvious improvement in uniformity from the ‘unadjusted’ upper plot of Figure 2.7 to the ‘DST adjusted’ middle plot. Also, shown in Figure 2.7 is the adjustment made for the time zone error. The entire profile is shifted 3 hours ahead for this home which is located in British Columbia. A similar plot was generated for each house in the dataset to visually confirm the adjustments.

2.5 DHW Consumption Characteristics

The data emerging from the Solar City program and NGTC provide a rare opportunity to observe and quantify patterns and trends in DHW consumption. In this section, average DHW consumption, the effects of occupancy, time of day, day of week, and seasonal effects are examined, along with a discussion of inter-household variability and distinct characteristic consumption patterns. The effects of these factors will be explored based on the Solar City data consisting of over 56 million measurements; the equivalent of about 5,600 household-weeks of data and the NGTC data consisting of over 27 million measurements; the equivalent of about 2,700 household-weeks of data.

2.5.1 Average Daily Hot Water Use

Average daily hot water use is perhaps the most fundamental metric of DHW, and with or without intra-day variations is used by building simulation software, including RETScreen and HOT2000 (CETC 2016b; CETC 2016a). This value is also simple and thus accessible for comparison with other studies and can be an indicator of changes over time. The average daily hot water use for the Solar City and NGTC homes is shown in Table 2.2 along with the results from other studies in reverse chronological order. The recommended/default values used in both RETScreen and HOT2000 software are also listed.

Table 2.2 Average daily DHW consumption and household occupancy

Source	Average Daily DHW Use (L/day)	Average Occupancy
Solar City (n = 119)	**172**	**3.83**
NGTC (n = 41)	**211**	**3.59**
RETScreen (CETC 2016b)	180[2]	3
Hot2000 v11 (CETC 2016a)[3]	188	3 (Default)
Edwards and Beausoleil-Morrison (2015)	189	-
Evarts and Swan (2013)	209	3.2
Swan et al. (2011)	208	-
Thomas et al. (2011)	186	3.35
Becker and Stogsdill (1990)	238	-
Perlman and Mills (1985)[4]	236	3.8

From Table 2.2, consumption seems to have generally decreased over the past three decades. It is also interesting to note that most of the more recent values based on measured studies (Thomas et al. 2011, Edwards and Beausoleil-Morrison 2015, and Solar City) are lower than the more recent values determined from DHW heating energy consumption (Evarts and Swan 2013 and Swan et al. 2011). However, the NGTC data do not follow this trend and indicate higher DHW consumption than any other measured study. Meanwhile, the Solar City data indicate lower DHW consumption than any other study. The installation of low-flow faucets and showerheads during the Solar City on-site survey, along with other factors mentioned in Section 2.3.1, may have contributed to this difference.

[2] RETScreen suggests a value of 60 L/day/person at 60 °C or 1/3 of the total water use shown on the water bill (CETC 2016b) The value shown in Table 2.2 reflects the estimated consumption for 3 occupants.

[3] HOT2000 has three faucet flow rates and the daily hot water consumption recommendation decreases to 177 L/day and 170 L/day for low flow and ultra low flow faucets respectively (CETC 2016a).

[4] This value corresponds to the average for ‘all families’ in the study, as opposed to the proto-typical family of 2 adults and 2 children.

The default DHW consumption values of both RETScreen and Hot2000 were updated in 2016 from 225 L/day and a default occupancy level of 4 (CETC 2008, CETC 2013, CETC 2016a, CETC 2016b). The updated software defaults align well with the DHW consumption estimates of these latest studies.

Distribution of average daily consumption across the 41 NGTC homes and the 119 Solar City homes is shown in Figure 2.8, with the associated statistics given in Table 2.3. It should be noted that although the average consumption is 172 L/day across all homes of the Solar City dataset, the majority of houses consume less than the average, with a median consumption of just 159 L/day. This is also true for the NGTC dataset, but the mean and median are more closely aligned at 211 and 204 L/day.

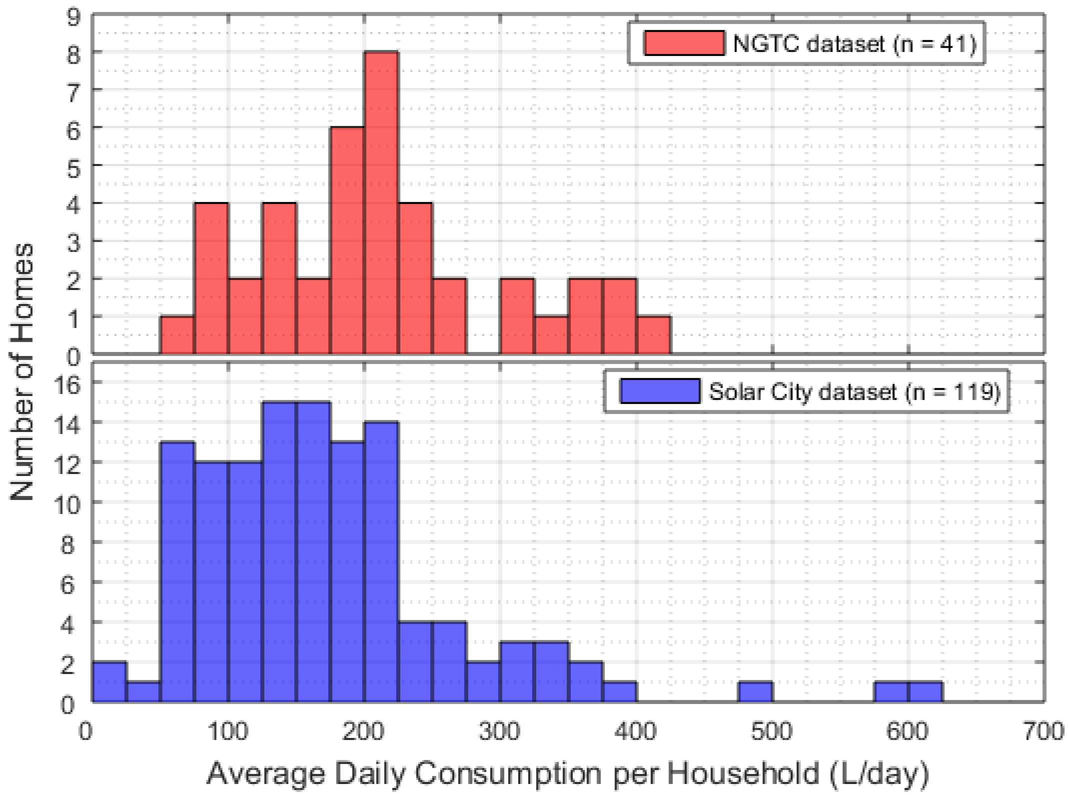

Figure 2.8 Distribution of average daily DHW consumption for the NGTC and Solar City datasets

Table 2.3 Statistical summary of the average daily DHW consumption per household

Statistic	NGTC (L/day)	Solar City (L/day)	Edwards and Beausoleil-Morrison (2015) (L/day)
Mean	211	172	189
Median	204	159	173
Maximum	401	615	438
Minimum	67	21	70
5th Percentile	81	59	-
20th Percentile	133	93	119
80th Percentile	272	220	245
95th Percentile	384	354	-

From Figure 2.8, there are some houses within the Solar City dataset which exhibit unexpectedly low and high DHW consumption. The Solar City house with the minimum daily average consumption of 21 L/day was a house of 2 occupants with data collected for 350 days. Of these, DHW consumption was non-zero for 337 days. The thirteen zero consumption days were neither continuous (as on a vacation), nor preferentially on weekends. The Solar City house with the maximum daily average consumption of 615 L/day has 9 occupants, with data collected for 328 days and DHW was consumed during every day of the measurement period. It is less likely that there will be days with zero DHW consumption for houses with higher occupancy levels since it is less likely that no occupant will be present on a particular day. For this reason, it is important to generate annual DHW consumption profiles separately for each occupancy level.

2.5.2 Effects of Occupancy

Occupancy has been shown to be a significant factor of influence on DHW use (Perlman and Mills 1985; Becker and Stogsdill 1990). This is shown in Figure 3 which plots the average daily consumption and occupancy for each house of the Solar City sample (red circles) and the NGTC sample (blue asterisks) as well as the average behavior across each dataset represented by the best fit lines.

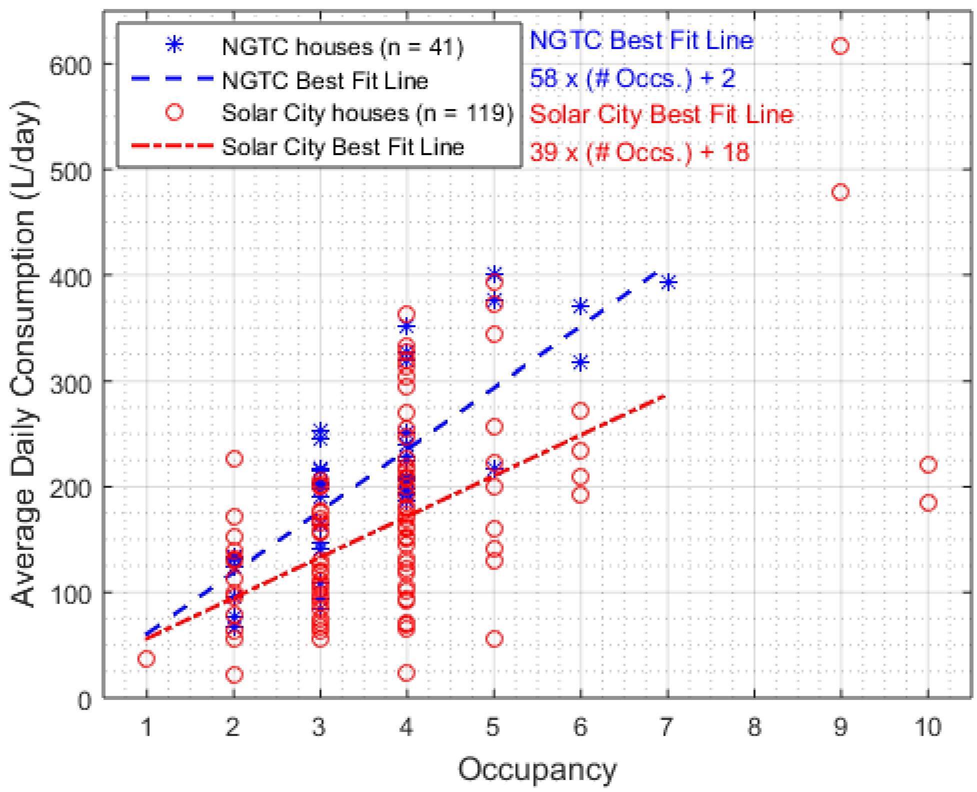

Figure 2.9 Occupancy distribution and average daily DHW consumption

From Figure 3, the two datasets both demonstrate a positive linear relationship between occupancy and magnitude of DHW consumption. Note that the population correlation for the Solar City dataset (looking at each individual house) had an R^2 value of 0.311, reflective of the distributions within each occupancy level. For the smaller NGTC dataset the population correlation had a stronger correlation with an R^2 value of 0.655. Though they do lie along the same line, the number of homes with 1 and 7 occupants (N = 1) is too small to add much confidence to these trends.

For higher occupancies in the Solar City dataset, the results varied greatly. It is suspected that at these high occupancies, the size of the hot water tank and the demographics of the household would affect DHW patterns, possibly limiting hot water consumption via supply constraints, though that would not fully explain the anomalously high consumption of the 9-occupant households. Both of these occupancy categories had very small sample sizes and therefore should not be considered representative.

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. Some building simulators such as Hot2000 use an occupancy based trend line to estimate average daily DHW consumption of a home, it is recommended that the Solar City trend line be used on account of the larger sample size and the application of modern flow reduction devices in the households.

2.5.3 Time-of-Use Variations

Previous studies have identified that time-of-use has an impact on energy required for DHW heating (Edwards and Beausoleil-Morrison 2015; Spur et al. 2006). Time-of-use patterns can be analysed on several scales. Thus, hourly, weekly, monthly and seasonal variations are explored in this section.

2.5.3.1 Hourly Variations

An average hourly consumption profile across all homes is shown in Figure 2.10 for the NGTC and Solar City datasets and is presented alongside the average hourly consumption found by Perlman and Mills (1985).

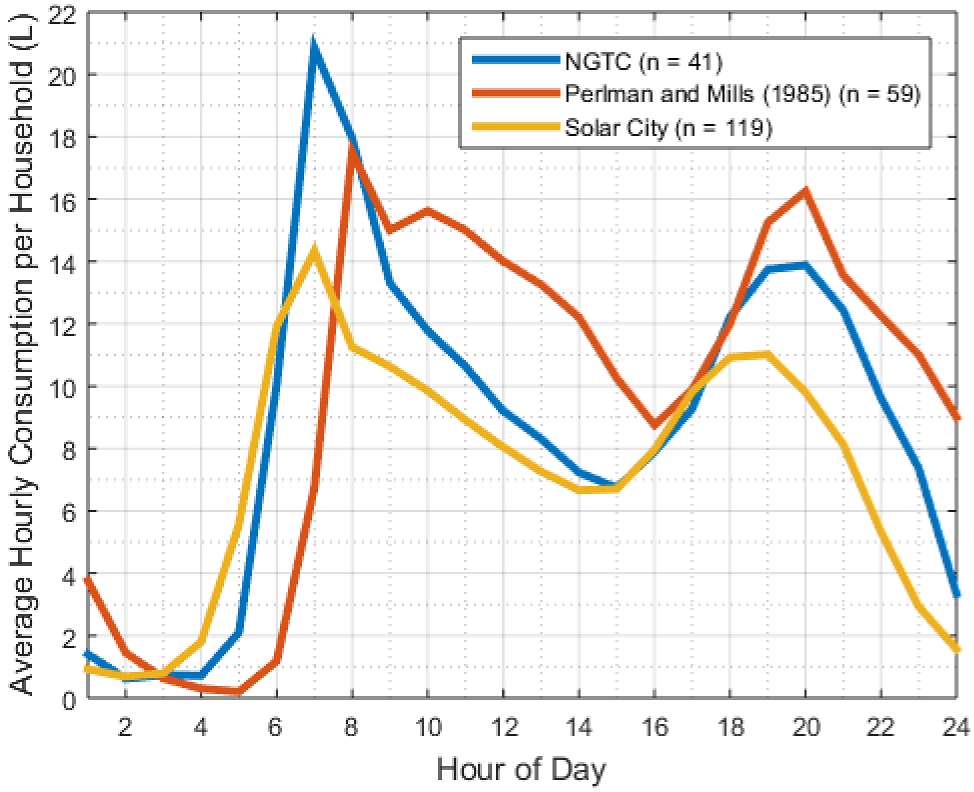

Figure 2.10 Average hourly household DHW consumption

As expected, consumption peaks in the morning, likely due to the use of showers, and again in the evening when occupants may generally prepare dinner and wash dishes. Consumption lessens during the mid-afternoon hours and reaches a minimum overnight. Consistent with the lower average daily consumptions, the Solar City and NGTC hourly values are generally lower than those published by Perlman and Mills (1985). However, the NGTC morning hot water consumption peaks at a value 23% higher than Solar City. It is also interesting to note that Solar City and NGTC morning hot water consumption peaks occur earlier in the day, with a morning peak between 6h and 7h as opposed to between 7h and 9h for Perlman and Mills (1985). This likely reflects demographic shifts, such as more 2-worker families. Many homes do not follow the average pattern, however, and some examples of consumption profiles from the Solar City dataset are shown in Figure 2.11.

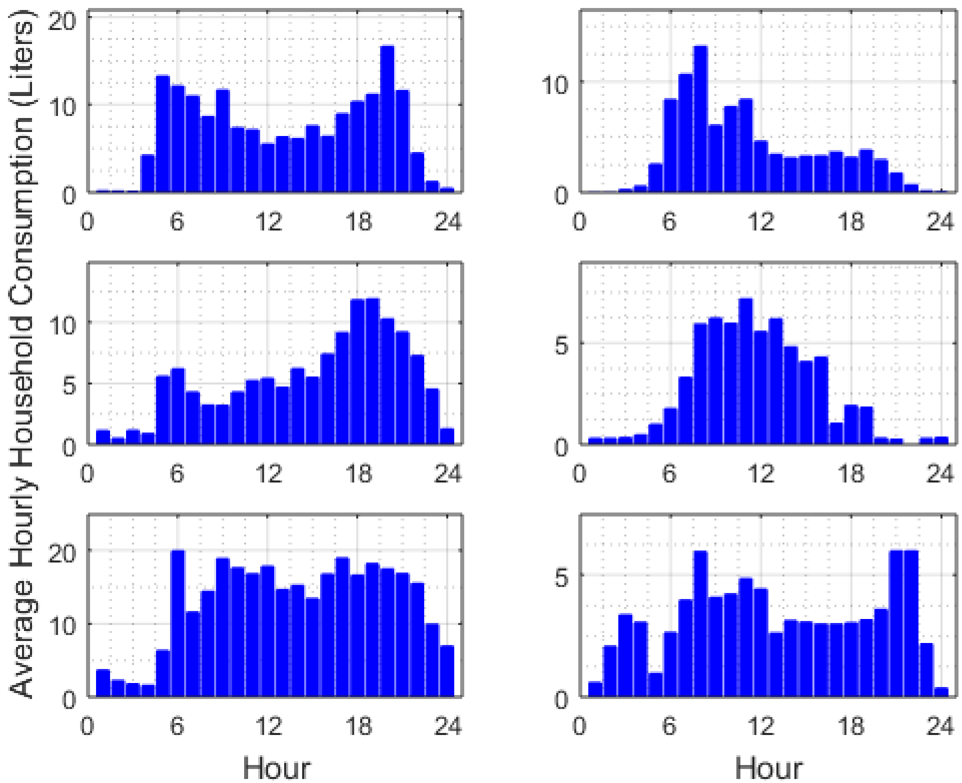

Figure 2.11 Examples of daily variations in DHW consumption from the Solar City dataset

Homes may be characterized by evenly weighted morning and evening consumption (top left), heavily weighted morning or evening consumption (top right and middle left, respectively), peak consumption at noon (middle right), evenly distributed daytime consumption (bottom left) and high overnight consumption (bottom right). These profiles reflect a true variability in consumption patterns throughout this sample of homes. A comparison analysis of consumption patterns was conducted by comparing the correlation coefficients of each house's average 24-hour consumption profile with the average 24-hour profile. This analysis did not reveal any clusters of typical patterns such as have been categorized in previous studies (Perlman and Mills 1985; Edwards and Beausoleil-Morrison 2015), but instead suggested that there is a continuous distribution of average hourly DHW consumption patterns that vary from the average. To further investigate whether or not there are clusters of predominantly morning or evening users, an analysis was conducted on all data (NGTC and Solar City) to evaluate the integrated morning consumption against the integrated evening consumption for each house. This is shown in Figure 2.12.

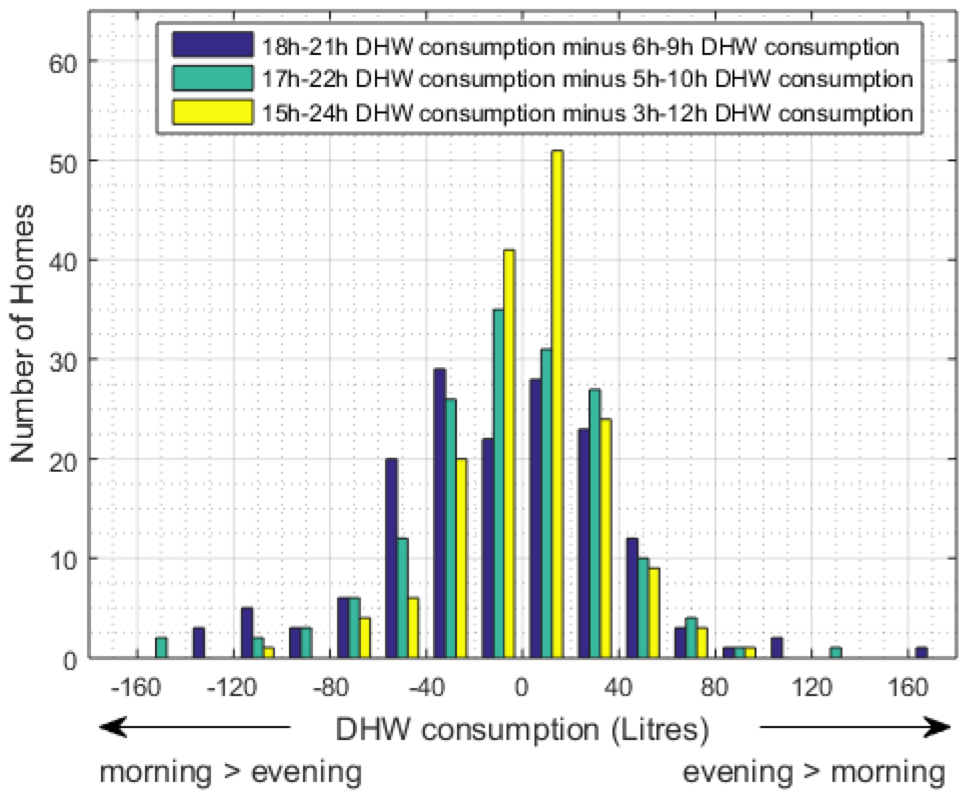

Figure 2.12 Evening consumption minus morning consumption for three time intervals for all Solar City and NGTC data

Morning and evening were each defined as intervals roughly centered around the morning and evening average hourly peaks (refer to Figure 2.10). Three interval lengths were chosen: 3, 5 and 9 hours in the morning and evening. For each house, the total average consumption during the morning time interval was subtracted from that of the corresponding evening time interval (e.g. total from 6h to 9h subtracted from 18h to 21h).

It is clear from Figure 2.12 that for each time interval there is a distribution of consumption patterns ranging from predominantly morning consumers to predominantly evening consumers. However, all three distributions are relatively normal and centered at zero; that is to say that the majority of homes consume comparable amounts of water in the morning and evening. As the interval is increased from 3 to 9 hours, the distribution becomes smoother and narrower. This suggests that over entire mornings (3h to 12h) and evenings (15h to 24h), DHW consumption is often equally weighted (when averaged over the length of the datasets). Furthermore, for any 'characteristic' difference between morning and evening consumption, this analysis shows that smaller differences are more common and that there is not a strong preference to morning or evening consumption amongst homes.

2.5.3.2 Weekly Variations

Due to the impact of weekdays (common workdays) and weekends (common day off work), there are variations in DHW consumption throughout the week. Daily average DHW consumption for each day of the week is presented in Figure 2.13.

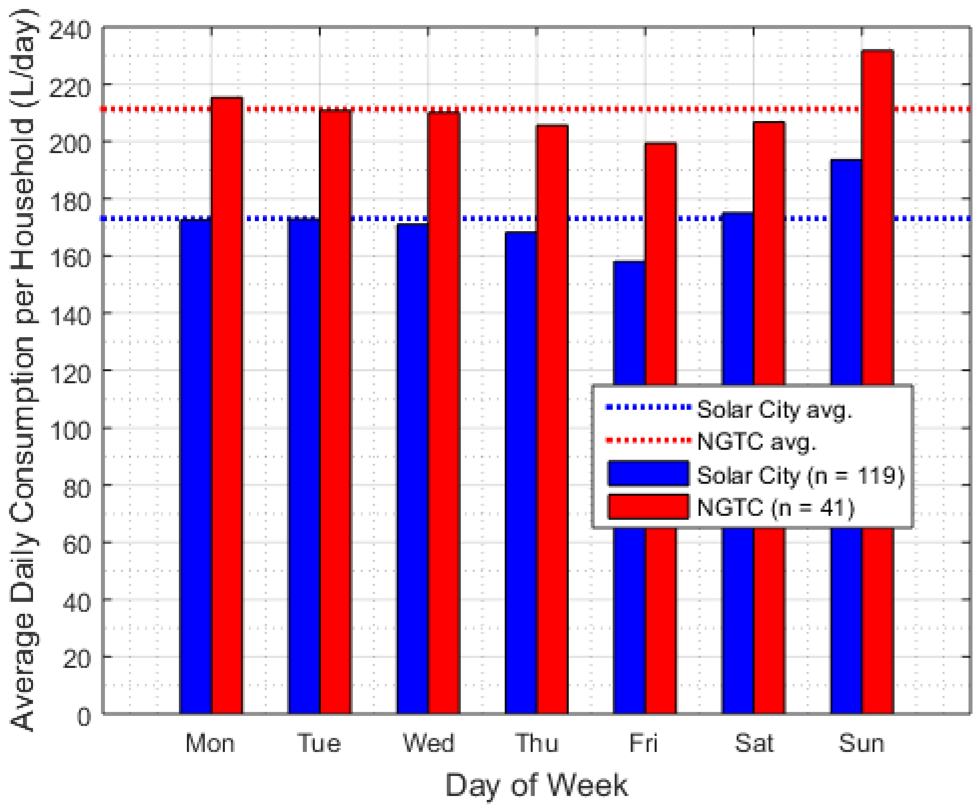

Figure 2.13 Weekly variation in DHW consumption for the Solar City and NGTC datasets

The Solar City and NGTC datasets follow a similar weekly pattern as shown in Figure 2.13. Two days stand out: Fridays exhibit the least consumption, though the temporal pattern of consumption on Friday is not notably different from other weekdays. Even more noticeable are Sundays, which is by far the most demanding hot water use day. Sunday consumption also differs from other days of the week temporally, likely due to the presence of occupants at home throughout the day. This effect is shown in Figure 2.14, which shows that Sunday morning consumption for the Solar City data peaks between 9h and 10h, about 3 hours later than on other days of the week. The NGTC data show the same effect (not shown).

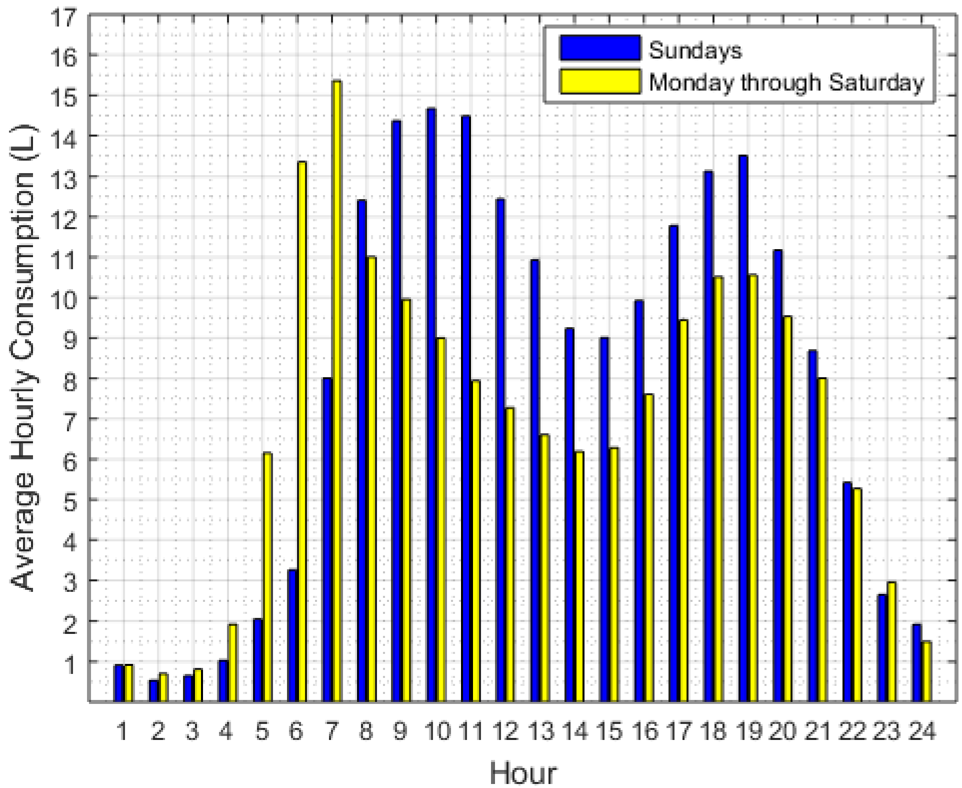

Figure 2.14 Average hourly DHW consumption on Sundays compared to Monday through Saturday for the Solar City data (n = 119)

2.5.3.3 Seasonal Variations

DHW consumption also varies seasonally. Perlman and Mills (1985) found that winter consumption can be up to 45% higher than summer consumption. Becker and Stogsdill (1990) found that the winter average consumption was 13% higher than summer average consumption. Our analysis investigated consumption in all four seasons defined in Table 2.4. Figure 2.15 shows the average daily consumption of both datasets for each season.

Table 2.4 Seasonal variations in DHW consumption

Season	Period	Number of days in the season
Winter	Dec 22 to Mar 20	89
Spring	Mar 21 to Jun 21	93
Summer	Jun 22 to Sep 22	93
Autumn	Sep 23 to Dec 21	90
Annual	Jan 1 to Dec 31	365

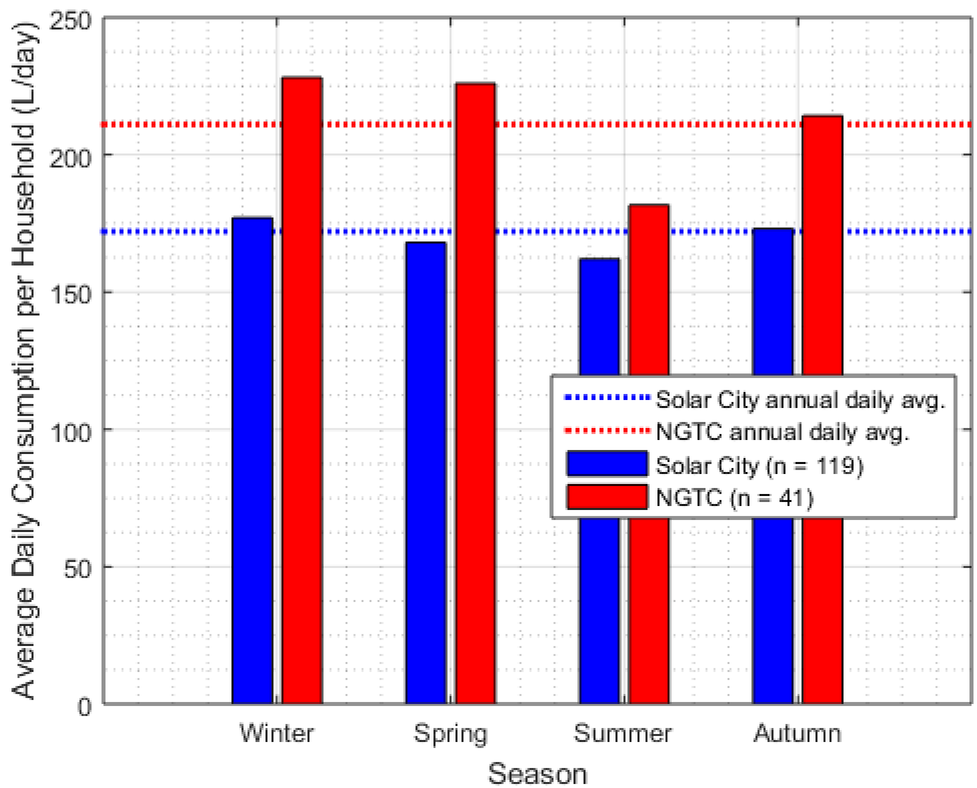

Figure 2.15 Seasonal variations in DHW consumption

The seasonal trends in Figure 2.15 generally match earlier findings: higher consumption during the winter season than the summer season. However, the NGTC consumption fluctuates more drastically than Solar City consumption. For Solar City, winter consumption is 9.6% higher than summer consumption and 2.9% above the average of 172 L/day, while summer is the season of lowest consumption at 5.8% below the average. For NGTC, winter consumption is 25.6% higher than summer consumption and 7.4%

above the average of 211 L/day, while summer is the season of lowest consumption at 14.5% below the average.

An increase in consumption during the colder seasons in the year may be a direct consequence of a lower ambient outdoor air temperature and thus a lower water temperature from the main water supply. Between December 22nd, 2014 and March 8th, 2015 the mean ambient outdoor air temperature was -5 °C for the region, while the mean summer temperature was 18 °C (Government of Canada 2015). With lower water temperatures from the main supply, occupants may be likely to use the hot water, or more hot water, for some tasks which would generally only need cold water (e.g. hand washing, dish rinsing).

2.5.4 Data Acquisition Systems

Data acquisition systems were installed by the NGTC as per a standard protocol. A typical system schematic is shown in Figure 2.16.

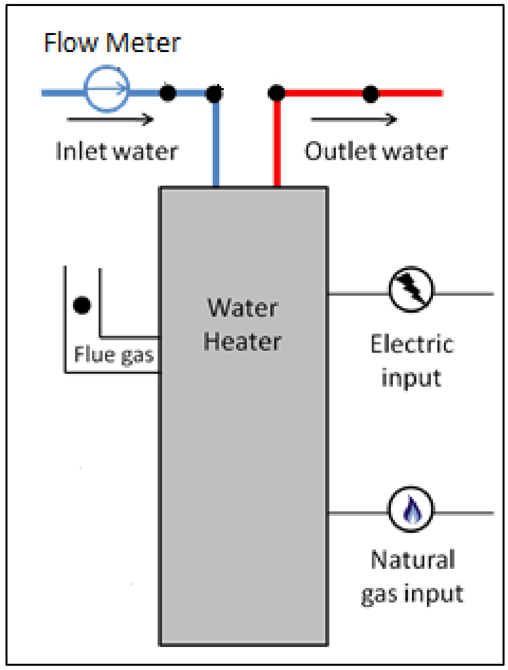

Figure 2.16 Schematic of a typical NGTC hot water heating system with data acquisition (adapted from a figure provided courtesy of NGTC)

The flow meters used were Omega FTB8007B-PT, valid for a range of 0.83 to 83.28 LPM (0.22 to 22 USGPM) with an accuracy of 1.5%. The meters operate on a multi-jet principle and utilizes a reed switch sensor (OMEGA Engineering Inc. 2015). Flow meters were installed on the cold water side (inlet) of the water heater. The data loggers employed were Hobo U30 data loggers which use a counter to accumulate pulses over a 1-minute period and apply a timestamp to this value (Onset Computer Corporation 2014).

There was concern about 'out-of-range' DHW flow, since the flow meter range has a minimum of 0.83 LPM. However, investigation into the 1-second time-step data described in Section 2.3.3 suggests that this is likely not an issue because over a 10-day period in one household, there were no 1-second DHW consumption measurements below 0.87 LPM.

2.6 Construction of Annual DHW Consumption Profiles

Hourly, weekly and seasonal variations in consumption, the features described in the previous subsections, are all embodied within annual profiles. It is important to construct a selection of annual profiles which represent a variety of temporal patterns of consumption. A statistical analysis found that there were no clusters of typical average hourly draw patterns (e.g. primarily morning or primarily evening consumers) but that instead there was an even distribution of varying consumption patterns throughout the day. Hence, it was determined that inter-household variability is most easily represented by supplying annual profiles for a selection of households. A method was developed to construct profiles at various occupancy levels (2 to 7 occupants):

- Homes which had both one year of measured data and associated occupancy information were selected (45 of 119 homes for the Solar City dataset and 37 of 41 homes for the NGTC dataset).

- For each of the selected houses, a complete year of 1-minute time-step data was constructed by cropping and data filling. Missing sections were populated with data from exactly one year later. If missing points still existed, then they were filled with data from one year earlier, one week later, one week earlier, two weeks later or two weeks earlier. For the Solar City and NGTC datasets, approximately 3% and 2% of datapoints were populated using this method, respectively.

- Each profile is matched with relevant meta-data such as the occupancy level and daily average DHW consumption. As well, if available, the DHW heating system type (e.g. conventional electric tank), the age of the home and the size of the home are given.

A total of 82 annual profiles were constructed using this method. Their characteristics are compared to those of the entire Solar City and NGTC datasets in the following subsection.

2.6.1 Annual DHW Profile Characteristics

To ensure the appropriate application of the new annual DHW consumption profiles, building simulators will want to understand their characteristics and origin. This section details the household 'meta-data' such as house location, occupancy, size of home and age of construction and compares their temporal characteristics with those of the entire Solar City and NGTC datasets.

2.6.1.1 House Locations

The annual DHW profiles come from five Canadian provinces spanning west to east. From Figure 2.17, 33% of houses are located in British Columbia, 6% are in Saskatchewan, 6% are in Ontario, 3% are in Quebec and 52% are in Nova Scotia.

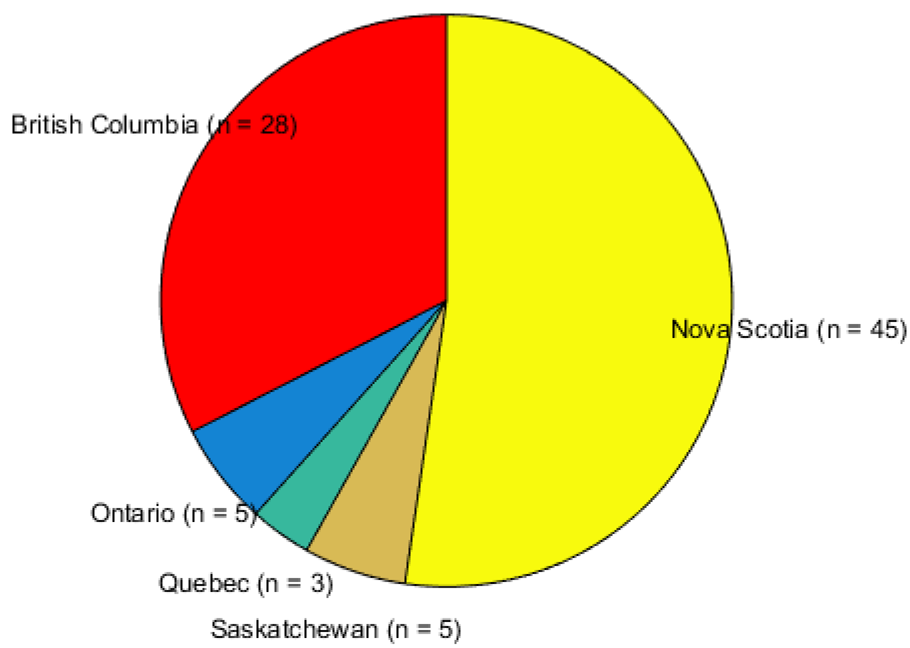

Figure 2.17 Annual DHW profile house locations by province

2.6.1.2 Household Meta-data

Figure 2.18 and Table 2.5 show the distributions and averages of occupancy, size of home and year of construction associated with the annual DHW profiles.

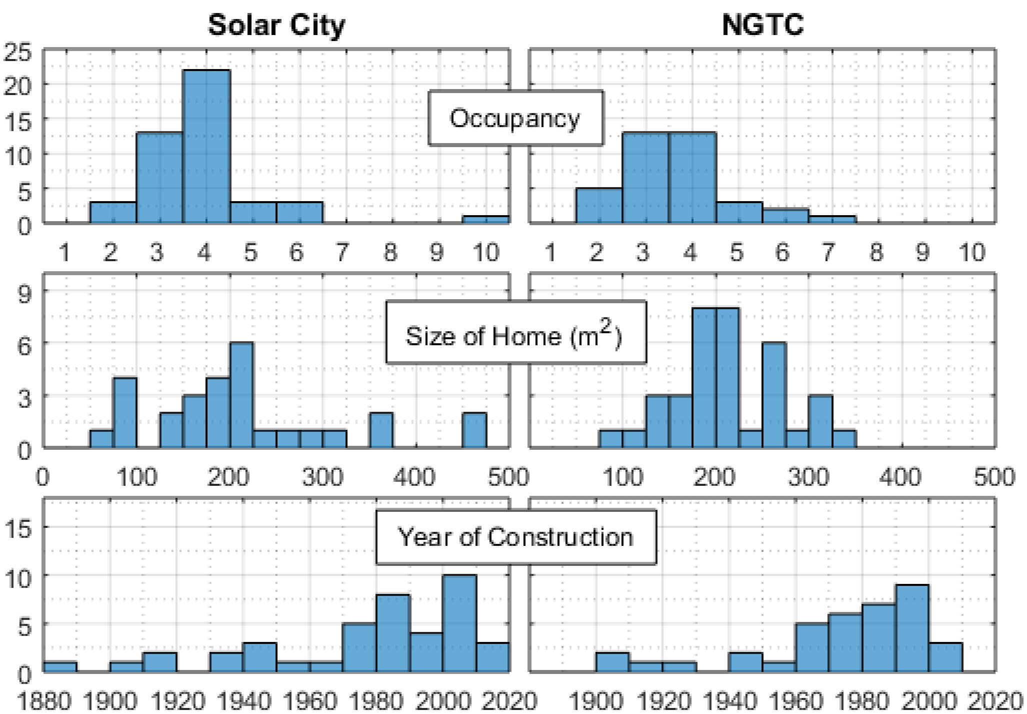

Figure 2.18 Distributions of occupancy, year of construction and size of homes for the Solar City and NGTC annual DHW profile datasets

Table 2.5 Meta-data summary of the Solar City and NGTC annual DHW profile datasets

Characteristic	Solar City	NGTC	Combined
Average Occupancy	3.9 (n = 45)	3.6 (n = 37)	3.8 (n = 82)
Average Year of Construction	1978 (n = 41)	1974 (n = 37)	1976 (n = 78)
Average Size of Home (m^2)	213.6(n = 28)	214.2(n = 36)	214.0 (n = 64)

As was shown in Section 2.5.2, DHW consumption is largely influenced by occupancy and from Figure 2.18 and Table 2.5, it should be noted that the average occupancy of 3.8 of is higher than the national average of 2.5 for private dwellings or 3.3 for single-detached houses (Statistics Canada 2013c). Age and size of home were not seen to be a major influence of DHW consumption, but it should be noted that both annual DHW profile datasets are from a wide range of house sizes and ages and are distributed around similar averages. The average house size of 214 m^2 (2303 ft^2) is much larger than the Canadian average of 133 m^2 (1431 ft^2) across all house types[5] or 158 m^2 (1701 ft^2) for single detached homes (NRCan 2014a).

2.6.1.3 Temporal Characteristics of Annual DHW Profiles

The temporal characteristics of the annual DHW profiles compared to the greater Solar City and NGTC datasets are also important. These are shown for the Solar City and NGTC datasets in Figure 2.19. Daily consumption statistics are shown in Table 2.6.

[5] House types are single detached, single attached, apartments, and mobile homes.

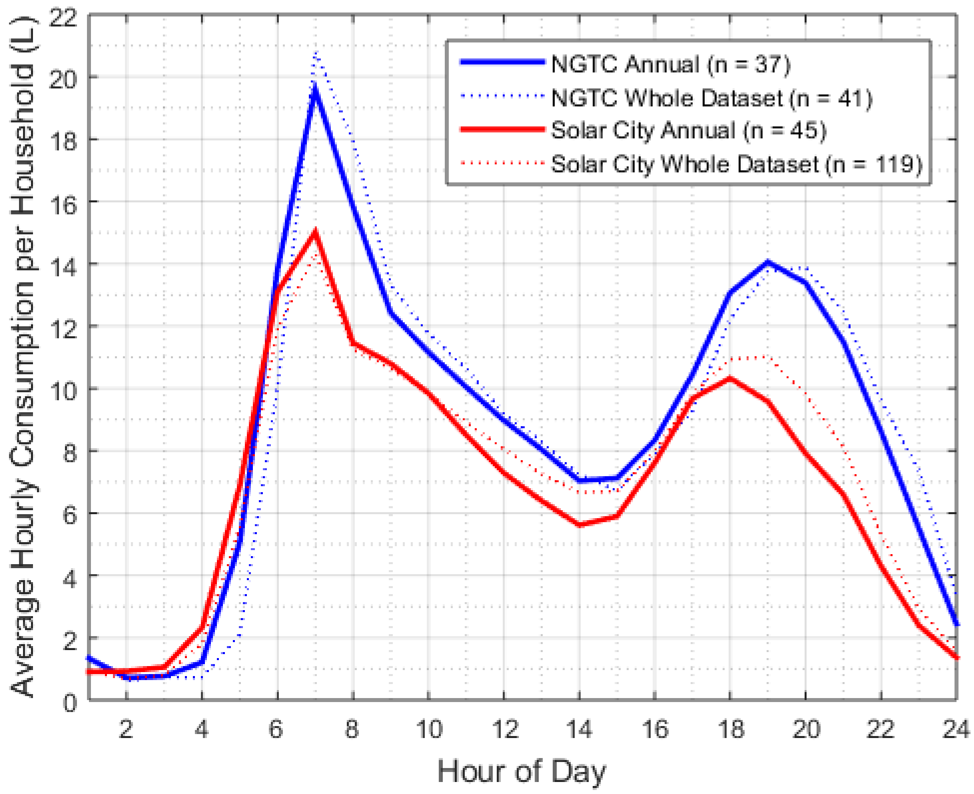

Figure 2.19 Average hourly household DHW consumption of annual DHW profiles

Table 2.6 Statistical summary of the average daily DHW consumption per household for annual DHW profiles

Statistic	Solar City (L/day) (n = 45)	NGTC (L/day) (n = 37)	Combined (L/day) (n = 82)
Mean	166	211	186
Median	157	197	186
Maximum	340	397	397
Minimum	23	68	23
5th Percentile	59	82	66
20th Percentile	100	132	105
80th Percentile	222	262	241
95th Percentile	327	389	360

From Figure 2.19 and Table 2.6, the NGTC annual dataset does not vary greatly from the complete NGTC dataset; the hourly profiles align closely and the daily average consumption is unchanged. The Solar City annual DHW profiles have an average consumption that is 3.5% less than the complete Solar City dataset and Figure 2.19 shows that this difference largely occurs in during mid-day and evening.

2.7 Conclusions

The measured data from NGTC and the Solar City project present a unique opportunity to investigate trends in DHW consumption because of their 1-minute time-step, multi-year duration, and 164 houses complete with occupancy information. The raw data revealed difficulties in interpreting flow rate measurements due to intermittent water draws. A new method for addressing these is described with the intention of applying it to other future measured datasets as they become available.

The analysis of this data revealed consumption characteristics such as varied average daily DHW consumption per household (Solar City = 172 L/day, NGTC = 211 L/day) and strong positive correlation with occupancy. Diurnal consumption patterns indicate an early morning start (6 to 7h) and continuously distributed morning and evening water usage, with a variety of consumption patterns illustrated. Sunday DHW consumption was significantly higher than that on other days of the week, and draws lagged weekday use by several hours.

From the Solar City and NTGC datasets, 82 new annual DHW consumption profiles at a 1-minute time-step have been generated, representing various time-of-use patterns and occupancy levels. The average daily DHW consumption across the annual DHW profiles is 186 L/day, which aligns well with other current studies of DHW use. They can be applied by building simulators to evaluate the performance of specific technologies across a variety of DHW user characteristics. Their use is demonstrated later in this thesis: Chapter 4 applies the profiles to evaluate tankless water heaters and Chapter 5 applies the profiles in a community scale simulation to evaluate community electricity demand.

Chapter 3 Appliance, Lighting and Plug Load Profiles of Canadian Homes

This Chapter was previously published as:

George, D. and Swan, L. G. (2016). A method for distinguishing appliance, lighting and plug load profiles from electricity 'smart meter' datasets. *Energy and Buildings*. In press. doi:10.1016/j.enbuild.2016.10.048

It has been included in this thesis under the terms of the license agreement with Elsevier. The copyright license agreement is provided in Appendix F.

Dane George is the principal researcher and author of the article. He conducted the research as part of his MASc. Thus, while he received supervision and guidance from his supervisor Dr. Swan, he carried out the work, wrote the published article, communicated with the editor of the journal, and carried out the necessary revisions before publication. The article has been edited and expanded upon to be integrated within this thesis.

3.1 Introduction

There is currently a strong focus on designing net-zero energy buildings and communities which use on-site electricity generation such as combined heat and power, and solar photovoltaics (PV) to supply energy end-uses. These buildings presently rely on the electricity grid as an infinite source and sink, and their proliferation necessitates a better understanding of impact upon time-step electricity demand. In net-zero energy communities, distributed generation from solar PV may cause severe peaks and valleys in the community electricity load as supplied by the grid. Utilities seek to understand these short-term demands so that they can procure sufficient generating capacity and install adequately sized and placed distribution equipment (e.g. polemounted transformers).

Existing models which employ building simulation software are capable of time-step energy demand estimation of buildings and communities. These typically rely on engineering principles to model space-heating and space-cooling, but ALP loads are largely driven by occupant behavior (stochastic), and modeling relies on measured or synthetic time-step load profiles. Examples of ALP loads are shown in Figure 3.1. Since

ALP electricity use varies widely across households, community scale modeling requires a sufficient number of unique ALP load profiles for individual houses to represent a greater community.

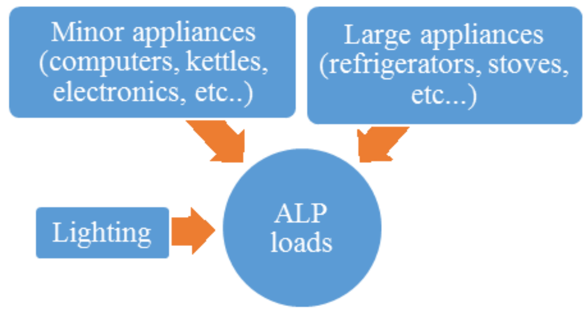

Figure 3.1 Examples of ALP loads

Currently, ALP profiles at high temporal resolution are rare. However, new datasets are increasingly available through utility "smart metering" programs. These usually consist of only the whole-house electricity load for homes, including ALP and ventilation, and potentially DHW heating and space heating/cooling, as shown by Figure 3.2.

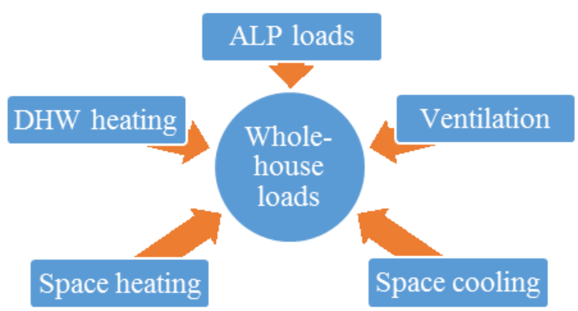

Figure 3.2 Examples of whole-house loads

Many homes rely on non-electric energy sources for DHW and space heating and do not cool or ventilate their spaces. These whole-house load profiles may be candidates to represent ALP loads only. This Chapter addresses this possibility by providing a new method of distinguishing houses which do not rely on electric space and DHW heating, or electric space cooling, from a database of whole-house electricity load profiles. The method is applied to a new dataset of 15-minute time-step whole-house electricity load measurements from 160 houses in Nova Scotia, Canada. The method relies on comparisons made with an existing research-grade dataset consisting of sub-metered 1-minute time-step electricity load measurements for 23 houses in Ottawa, Canada. The benefits and limitations of this method are explored based on additional comparisons between the newly distinguished profiles and the existing research-grade profiles. This method presents an opportunity to distinguish profiles from the whole-house database that can adequately represent ALP loads for building simulation purposes.

3.2 Background and Literature Review

In an effort to design buildings with minimal environmental impact, the implementation of net-zero energy buildings at a community scale may have economic advantages and utilitarian benefits. For example, smart grid technologies may allow for power sharing technologies which can help control utility demand. To date, performance evaluations of net-zero energy communities are still uncommon, but it is expected the electrical grid interaction with these communities will present new challenges. For example, on-site solar PV electricity generation and community electricity demand of net-zero energy communities may not align, causing dramatic changes in the community load profile (Hachem-Vermette et al. 2015).

Previous community scale modeling endeavours have relied on a limited number of electricity profiles, scaled up to represent a larger number of homes (Swan et al. 2011). This may allow for accurate estimation of annual, monthly, weekly or even daily energy consumption, but does not allow for time-step demand modeling at hourly, 15-minute or 1-minute time-steps. This is because the scaling up of a limited number of profiles will result in unrealistic peaks and valleys in demand which follow the temporal patterns of the limited profiles. This is demonstrated in Figure 3.3 with some of the ALP profiles which will be introduced in Section 3.3.1 of this Chapter. In this figure, the ALP profile for 1 house is scaled by a factor of 22 and compared to the sum of 23 unique house profiles. It is evident that the realistic summing of unique profiles produces far less dramatic changes in total demand than the unrealistic scaling of a single or few profiles.

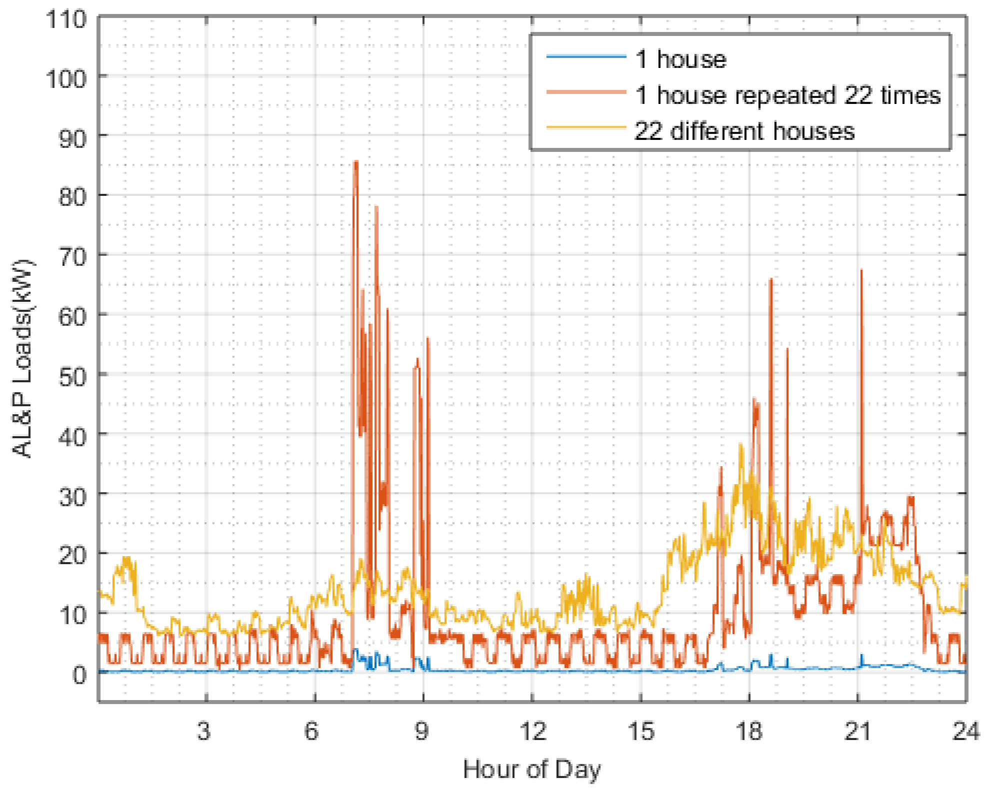

Figure 3.3 Electricity demand comparison of scaling one house by 22 versus summing 22 unique houses

As an alternative to expensive field studies that collect sub-metered electricity load measurements, researchers have generated synthetic electricity load profiles for building simulation. For example, Armstrong et al. (2009) created a set of nine, 5-minute time-step ALP electricity demand profiles designed to represent 'typical' detached Canadian households. The purpose of the profiles, however, was not to examine grid effects or demand side management with building simulation tools, but instead to look at system performance in terms of ability to meet heating and electrical requirements of the house.

In constructing these profiles, engineering assumptions were made; for example, to better represent detached homes as opposed to row housing, the quantity of appliances per household and its associated electricity use were adjusted upwards from the values drawn from appliance stock surveys. When compared to measured profiles, the synthetic profiles show a higher concentration of small loads (<200 W) and should have a higher constant baseload to match the measured profiles (Armstrong et al. 2009). These profiles have since been applied in many building energy models (Leadbetter and Swan 2012, Obrien et al. 2011). While they are good for aggregate electricity consumption analysis, their limited number is insufficient for community time-step demand analysis because of the scaling issue previously demonstrated.

Wills et al. (2016) developed a set of synthetic separate appliance and lighting load profiles at a 1-minute time-step resolution using the open source Microsoft Excel based model developed by Richardson et al. (2009) and Richardson et al. (2010). The original models were constructed based on individual appliance and lighting data and U.K. based ownership and time-of-use statistics. However, the models were made to be easily adaptable to future changes, such as technological advancements of appliances. Furthermore, various elements in the models could be adjusted, such as lighting and appliance units and total and active occupancy. This allows the models to generate any number of profiles to represent multiple categories of homes. Output comparison with measured data from 22 U.K. homes suggested a good representation of diversity of demand between profiles and fluctuation of demand from minute to minute was well represented in the mid-range (100 W to 1000 W) while small and large transitions are underrepresented (10 W to 100 W and over 1000 W) (Richardson et al. 2010).

Using the above models, Wills et al. (2016) generated a set of 50 appliance and 50 lighting profiles for four Canadian regions (Atlantic, Ontario, Prairies, and British Columbia). The original model inputs were replaced with new values based on Canadian appliance characteristic and appliance stock data as well as baseload observations of measured ALP datasets of Saldanha and Beausoleil-Morrison (2012) and Johnson and Beausoleil-Morrison (2016). However, no time-of-use surveys were available for the Canadian context, so observations from the U.K. time-of-use surveys were maintained in the model. All the profiles in each region were assigned the same annual appliance and annual lighting energy use based on a Canadian average for the region. This obviously does not allow for variation of annual demand between homes.

In recent years, many studies have emerged in Canada and abroad examining measured residential electricity loads. ALP loads have been shown to be primarily behavior driven with a weak relationship to outdoor temperatures and can vary significantly across households (Aydinalp-Koksal et al. 2015, Chen et al. 2015, Lee et al. 2014). These observations reinforce the need for a variety of unique and representative profiles, especially for community-scale simulation. Furthermore, plug-loads are constantly changing as new electricity consuming devices become available or more affordable to various demographics (Firth et al. 2008). Such trends strongly support the continued collection and publication of up-to-date electricity consumption profiles for building simulation. Sub-metered, strictly ALP load measurements are still uncommon and existing profile disaggregation techniques require intrusive appliance specific knowledge (Basu et al. 2015, Zeifman and Roth 2011). However, the increasing availability of whole-house load profiles presents an opportunity to satisfy the demands of building simulation with a selection of these profiles. The remaining sections of this Chapter explore this possibility.

3.3 Data Sources

3.3.1 Sub-metered Electricity Data for Ottawa, Ontario, Canada

The Ottawa dataset was provided by the Sustainable Building Energy Systems research group at Carleton University. A complete description of the dataset measurement techniques, quality and processing can be found in Saldanha and Beausoleil-Morrison (2012) and Johnson and Beausoleil-Morrison (2016).

Beginning in 2009, measurements of whole house and individual device consumption (DHW, furnace, space cooling) were taken for more than a full year at 1-minute time-steps for 12 single-detached Canadian homes in Ottawa, Ontario. The instruments were then recommissioned in 2011, and an additional 11 row houses were added for another full year. All gaps and data quality issues were addressed to create 22 continuous annual ALP profiles[6]. For all houses, furnace auxiliary, air conditioner (for space cooling) and DHW consumption were subtracted from whole house consumption to produce a 'non-HVAC' or ALP equivalent electrical consumption profile for each house. Additionally, in some homes sub-metering was conducted on the dryer, stove, dishwasher and an auxiliary electric heater. However, there is no mention of whole-house ventilation systems such as heat recovery ventilators. With 7 of the homes being constructed in 2000 or later, a ventilation system load is likely included in the ALP load profiles on account of building code requirements.

For these datasets, two quality issues arose requiring data processing. Firstly, there were periods of missing data. If available, these sections were filled with data for the same days and times from the previous or following year. When this was not possible, the sections were filled with data corresponding to the same time-period in a day in "as close proximity to the missing record as possible". Secondly, there was a minimum resolution power[7] that could be detected by the measurement equipment so that periods of very low power draw would result in some measurements of zero power draw. A data smoothing process was used to correct this issue. For the data collected in 2011 and 2012, the data contained negative ALP values (0.17% of values). These were assumed to be associated with

[6] ALP profiles creation was not possible for one house where an electric DHW heater was not sub-metered.

[7] Three different current transducers rated at 30 A, 50 A and 100 A were used to measure electric draw of various circuits, resulting in minimum power measurement resolutions of 45 W, 75 W, and 150 W respectively. See Saldanha and Beausoleil-Morrison (2012) for greater details.

equipment measurement error during the periods of low draw which then became negative values during the ALP load derivation. These values were treated as zero power draws for the purposes of this study.

As part of their study, Saldanha and Beausoleil-Morrison (2012) conducted a comparison analysis of the derived ALP profiles with the synthetic profiles generated by Armstrong et al. (2009). The probability distribution of the measured data was contrasted to that of the synthetic profiles and it was found that the synthetic profiles did not adequately capture the temporal variability within each of the measured profiles or the variation between households. It is suggested that that further development of synthetic profiles draws from characteristics of more measured profiles.

Johnson and Beausoleil-Morrison (2016) examined the factors influencing ALP consumption levels across all of the 23 houses and found that house size (floor area) had weak influence while occupancy strongly influenced annual ALP electricity consumption. They also compared the 23 house dataset with the Ontario housing stock data published by Natural Resources Canada (NRCan 2012, NRCan 2013) and found that the ALP electricity consumption of homes between the 25th percentile and 75th percentile (i.e. half of the measured houses) are in close agreement with the Ontario housing stock data.

3.3.2 Whole-house "Smart Meter" Data for Nova Scotia, Canada

The Nova Scotia dataset is whole-house electricity demand measurements at 15-minute time-steps obtained from smart meter data provided by electricity utility Nova Scotia Power Incorporated (NSPI). Data were labeled and divided into three categories of homes:

- All-electrically heated (AEH) homes which rely on electricity as the primary heating energy source, either via resistance strip heaters or heat-pump systems.

- Non-electrically heated (NEH) homes which rely on natural gas, oil, propane, or wood as the primary heating fuel. Electricity may still be used as a secondary heating source.

- Time-of-use electrically heated (TOU) homes which rely on electricity as the primary heating energy source via an electric thermal storage (ETS) unit. The unit charges overnight during off-peak pricing hours, and discharges during the day on-peak pricing.

Houses were assigned to a category based on the status of the heating system at the time of the smart meter installation and the information may no longer be valid if a new system has been subsequently installed. Such evolution of the housing stock is typical, and must be expected to influence the results of whole-house electricity consumption datasets. Furthermore, an air conditioning system may be present in any home category for space cooling.

While the TOU homes had a ‘smart meter’ installed in order for them to participate in an alternative pricing scheme, it is unknown how the remaining houses were selected to have ‘smart meters’ installed. Any biases associated with the selection process are unknown for this study.

Meta-data was provided for 34 out of the 160 homes based on a telephone survey conducted by NSPI in the fall of 2014. Primary and secondary heating system type and energy source, cooling system (e.g. ceiling fan, portable fan, air conditioner), occupancy, main living area size, and location (town) were recorded. Of these homes, 24 relied on electricity as the primary heating source, 7 relied on oil and 3 relied on wood or wood pellets. Three of the 7 homes which relied on oil for heating also had plug-in electric heaters as a secondary source. Thirteen of the homes (38%) had an air conditioner for space cooling, 16 of the homes (47%) had only portable or ceiling fans for cooling, and 5 of the homes (15%) had no cooling system. Total occupancy averaged 2.7 people per house. Only 25 homes provided a main living area estimate and the average house size is 184 m^2 (1983 ft^2). The 34 homes were located in various cities, towns, and villages spread throughout Nova Scotia.

Data was provided for the years 2012, 2013, and 2014 for a total of 160 house profiles although not every house participated for all three years. Table 3.1 summarizes data availability.

Table 3.1 Availability of Nova Scotia data by home category

House Category	Year		
	2012	2013	2014
	Number of Homes		
AEH	74	62	53
NEH	53	42	32
TOU	29	28	24
Total	156	132	109
Full years of data	1 yr.	2 yrs.	3 yrs.
Number of houses	28	29	104

The electricity measurement instruments were electronic ALPHA PLUS® Meters. The meter's process voltages and currents into energy pulses in units of watthours. These are processed by a microcontroller to produce a demand (load) measurement over a time interval (set to 15-minutes for this dataset). Each measurement datapoint is the total accumulated energy over the interval (in kWh), over the time interval. These meters are revenue-grade and operate with a measurement accuracy of 0.2%.

3.4 Methodology

First, the datasets are compared with the intention of identifying homes from the Nova Scotia dataset that do not use electricity for space heating and cooling, so that these whole-house profiles may be treated as ALP loads and used in building performance simulation. The obvious starting point is to use the NEH homes from the Nova Scotia dataset. Because space conditioning strongly depends upon ambient air temperature, the seasonal variations are compared in Figure 3.4. Nova Scotia AEH and TOU homes have also been added for comparison.

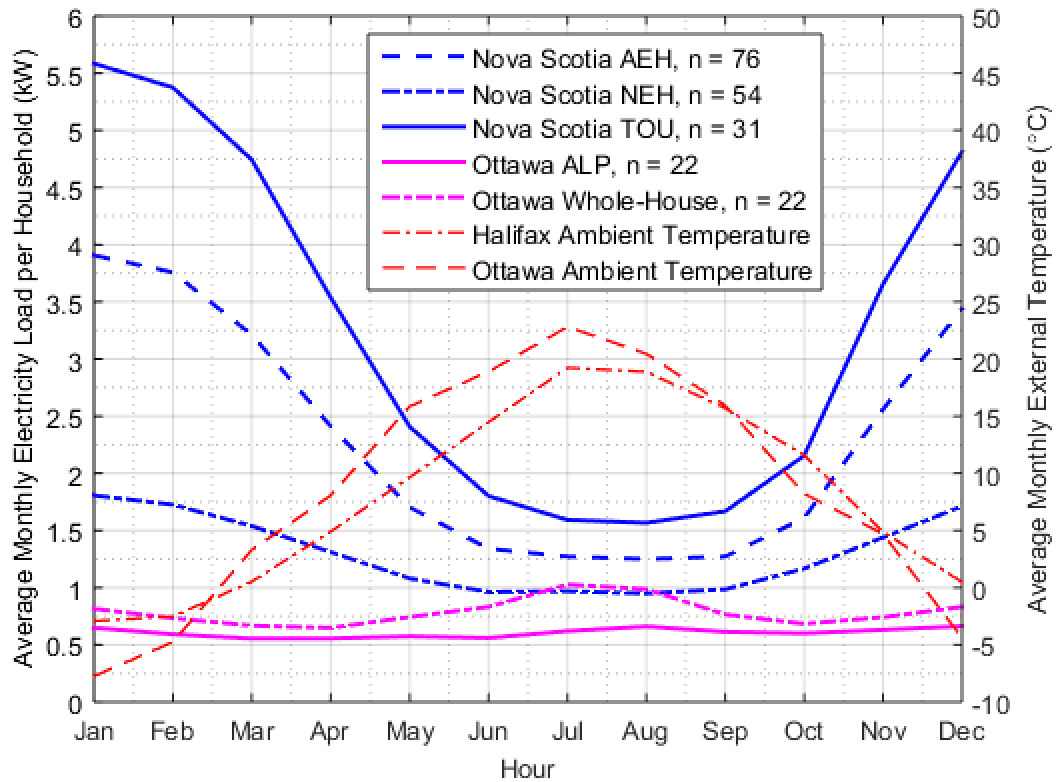

Figure 3.4 Average monthly electricity demand and ambient temperatures for Ottawa and Nova Scotia datasets

In Figure 3.4, the monthly average ambient temperatures in Halifax and Ottawa have been plotted to demonstrate the relationships with measured electricity usage. There is only a minor correlation between external temperatures and the Ottawa ALP electricity loads (R = -0.19). The whole-house loads show a clear relationship to outdoor temperature (R = 0.46). This is expected, since the whole-house load includes power supplied to air conditioning units. However, an increase in electricity demand occurs during the colder months as well, because the whole-house loads include the power draws from the heating system auxiliaries such as furnace fans and boiler pumps. There is a strong negative correlation between the external temperature in Halifax and the Nova Scotia whole-house NEH electricity loads (R = -0.96) suggesting that as the temperature drops, the electricity demand increases. On average, electricity use for the NEH homes increases by about 80% from the warmest months to the coldest months. These results suggest that some of the NEH houses from the Nova Scotia dataset still rely on some form of auxiliary electric heating. This heating effect is much more dramatic with the Nova Scotia whole-house AEH and TOU electricity loads, which increase by about 250% (AEH) and 350% (TOU) from the warmest months to coldest months.

After generating a monthly average load profile for each individual house in the Nova Scotia dataset, it is revealed that many of the houses had a relatively constant load across the seasons, following the ALP trend of the Ottawa data. An individual house analysis showed some of the monthly profiles of homes in the NEH category were strongly affected by ambient temperatures. As well, some homes in the AEH category were not affected by outdoor temperatures, likely caused by heating system retrofits. Consequently, these homes profiles may actually represent only ALP loads and so all categories of homes are included in the following analysis.

3.4.1 Identification of Homes with Electric Space Heating

This section describes the method used to distinguish homes from the Nova Scotia dataset that do not rely on electric space heating, based on trend observations from 22 Ottawa dataset ALP profiles.

To distinguish these houses, the average load for the mild season months (Jun, Sep) was subtracted from the average winter load (Nov – Feb) for each house in both datasets. Due to the mild temperatures, it is assumed that there is the least likelihood of space heating or cooling during the selected summer months and so they are chosen as the 'baseline months'. The results are plotted in histograms, shown Figure 3.5.

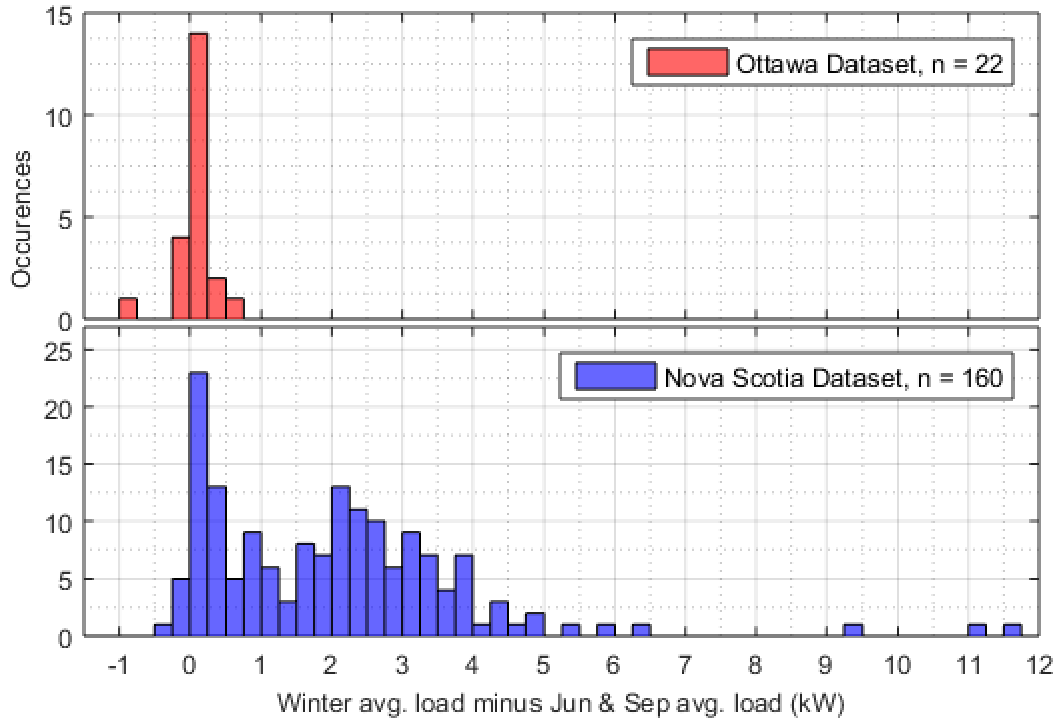

Figure 3.5 Histograms of average winter load minus average Jun and Sep loads for Ottawa and Nova Scotia datasets

The upper histogram in Figure 3.5 shows that the Ottawa ALP winter load does not vary greatly from the shoulder season load, with a difference between the averages ranging from -0.8 kW to +0.6 kW. In the lower histogram, the Nova Scotia dataset differences range from -0.4 kW to +11.5 kW. There are two major peaks, one occurring at about a +0.5 kW difference and the other occurring at about +2.5 kW. The distribution in proximity to the 2.5 kW peak is a relatively normal distribution, likely representing electrically heated homes of various sizes and with various heating system efficiencies. The homes distributed around the +0.5 kW peak are likely the homes which do not rely on electric heating.

All Nova Scotia homes which showed an average load difference of less than +0.6 kW were assumed to be homes which do not rely on electric heating. The 45 qualifying homes were selected to represent non-electrically heated home profiles. Due to the overlapping nature of the non-electrically heated and electrically heated home distributions, it is expected that a small number of homes may be mislabeled. For example, a home which engages in minor amounts of electric space heating with a small unit heater may be recognized as a non-electrically heated home. Conversely, a non-electrically heated home where the homeowners vacation primarily during the shoulder seasons might be recognized as an electrically heated home.

3.4.2 Identification of Homes with Electric Space Cooling

This section describes the method used to distinguish homes from the Nova Scotia dataset that do not rely on electric space cooling. The method is similar to the method described in Section 3.4.1, but has been further refined based on trend observations from 22 space cooling load profiles from the Ottawa dataset.

All space cooling load profiles are associated with central air conditioners and do not include the fan load required to circulate air through the households. Across households there was a wide range of use of space cooling. Statistics of annual space conditioning electricity consumption and average air conditioner loads[8] are shown in Table 3.2.

[8] The air conditioner load is considered to be the load when the air conditioner is engaged. So, only significant loads are considered. Space cooling profiles consisted of many very small load measurements which are not representative of an active air conditioner. All loads above 0.015 kW were considered for the purposes of Table 3.2.

Table 3.2 Statistical summary of the average daily electricity consumption per household for two datasets

Statistic	Statistics of Annual Space Cooling Electrical Consumption, n = 22 (kWh /year)	Statistics of Average Air Conditioner Loads, n = 22 (kW)
Mean	537.3	1.66
Median	534.9	1.57
Maximum	1337.0	2.63
Minimum	21.8	0.99
5^{th} Percentile	55.2	1.00
20^{th} Percentile	150.5	1.16
80^{th} Percentile	890.0	2.12
95^{th} Percentile	1123.6	2.53

From Table 3.2, some houses used very little electricity for space cooling annually while others use much more (21.8 kWh/year to 1337.0 kWh/year). In contrast, the range of average air conditioner loads was much smaller (1.00 kW to 2.63 kW), suggesting that low consuming households did not engage their air conditioners very often. Such households would be very difficult to identify from a larger whole-house load dataset such as the Nova Scotia dataset because the space cooling load would not be significant enough in magnitude or overall energy consumption to noticeably influence the whole-house load. However, the space cooling load of the higher consuming households would likely have a greater impact on a whole-house load during the certain times of the cooling season. To explore this further, Figure 3.6 investigates the time-of-use characteristics of the Ottawa space cooling load profiles.

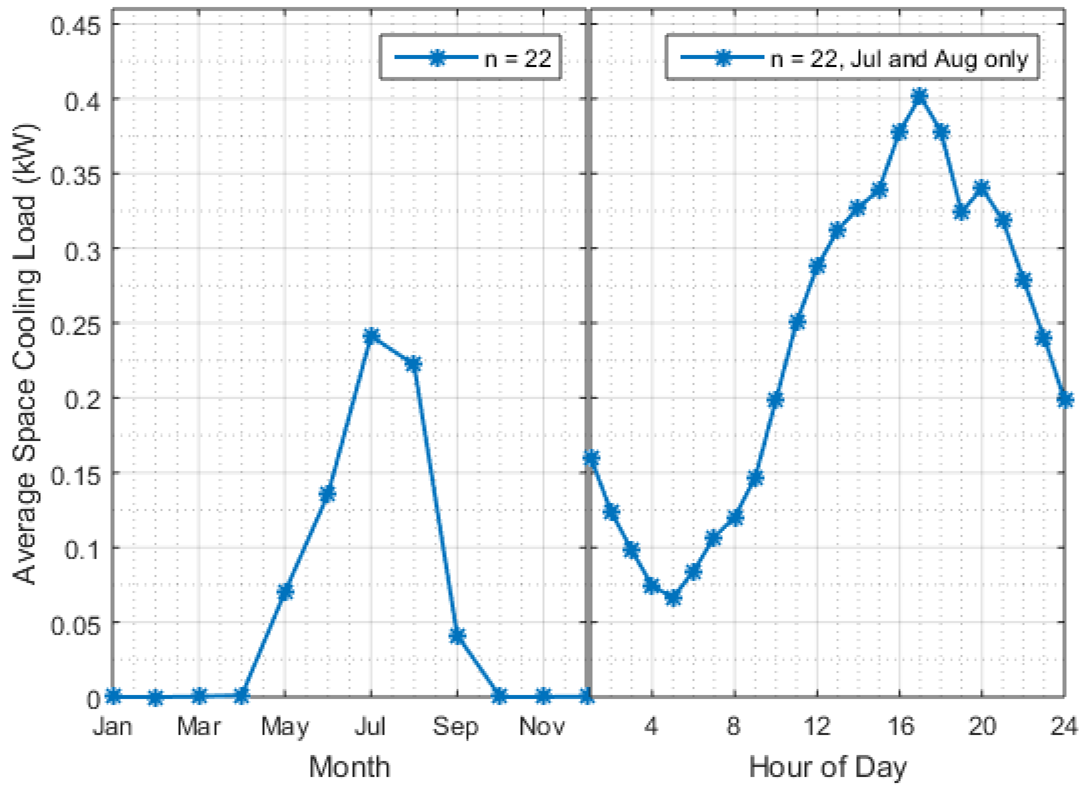

Figure 3.6 Average monthly space cooling load and average hourly summer space cooling load for the Ottawa dataset

From the plot on the left of Figure 3.6 of the monthly average across all datasets, space cooling loads ramp up during May and June, peak in July and August and drop significantly in September. The plot on the right of Figure 3.6 shows the average hourly space cooling load over the peak cooling months of July and August. The load is highest during the afternoon and evening (13h to 21h) which lags behind the sun's trajectory through the sky by approximately 4 hours, presumably due the thermal mass of the buildings. A more specific peak occurs at 17h and is likely associated with occupants returning home at the end of a workday. These observations are now applied in a method to distinguish homes from the Nova Scotia dataset that do not rely on electric space cooling

The average evening load for the mildest shoulder month (Sep) is subtracted from the average summer load (Jul - Aug) for all profiles of four datasets: Ottawa space cooling, Ottawa ALP and Ottawa combined ALP and space cooling and Nova Scotia whole-house. Evening is considered to be the peak hours from Figure 3.6 (16h – 18h). The results are plotted in histograms, shown Figure 3.7.

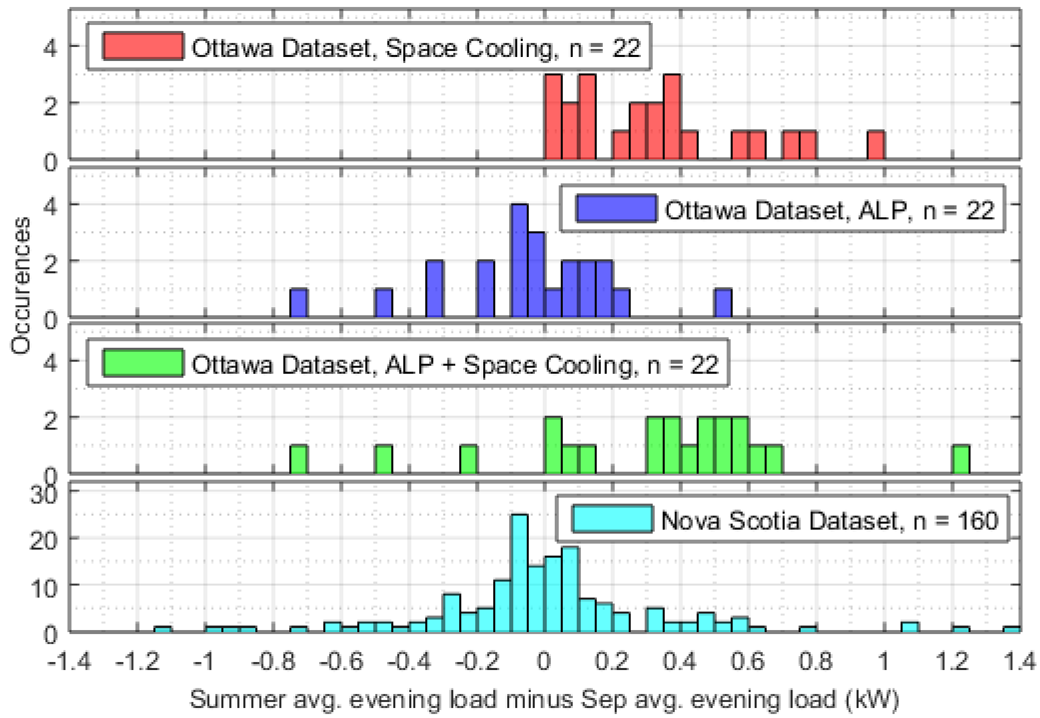

Figure 3.7 Histograms of average July and August evening loads (16h – 18h) minus average September evening loads for Ottawa and Nova Scotia datasets

The upper histogram in Figure 3.7 shows that the summer evening space cooling loads range in difference from the September evening space cooling loads from nearly 0 kW to +1 kW. Meanwhile, in the second histogram from the top, the majority of the ALP load differences are shown range from -0.4 kW to +0.2 kW. When the loads are combined in the third histogram from the top, the effect of the space cooling load is clear because many of the load differences are above +0.2 kW. In the lower histogram, the Nova Scotia dataset differences range from -1.2 kW to +1.4 kW.

All Nova Scotia homes which showed an average load difference less than +0.25 kW were assumed to be homes which do not rely on space cooling. It is suspected that homes which engage only a minimal amount of space cooling may not have been identified by this method, as shown by the upper histogram in Figure 3.7. Furthermore, some homes which do not rely on space cooling may have also been eliminated (note the outlier at +0.5 kW in the second histogram from the top in Figure 3.7).

Of the 160 homes in the Nova Scotia dataset, 24 (15%) were found to rely on space cooling. This is much less than the average in Nova Scotia where the penetration of air conditioners in homes is approximately 28% (NRCan 2014a), but this is expected because this method fails to eliminate homes which engage in small amounts of space cooling. Only 4 of 45 (9%) of the non electrically heated houses selected in Section 3.4.1 were found to rely on space cooling. This is an even lower fraction, but it should be noted that during the previous step of eliminating houses that are electrically heated, a large number that are electrically cooled may have been eliminated as well (consider that heat pumps can provide both heating and cooling).

3.4.3 Identification of Homes with Electric DHW Heating

This section describes the method used to distinguish homes from the Nova Scotia dataset that do not rely on electric DHW heating. The Ottawa dataset included load measurements from one electric DHW heater and this method is based on trend observations this profile.

To provide context to the problem, the significance of time-step interval length is first explored. The electric DHW heater load profile of the Ottawa dataset is plotted for a 5-hour period at both a 1-minute and 15-minute time-steps shown in Figure 3.8, along with the whole-house and ALP load profiles for the same home. Note that only two homes of the Ottawa dataset relied on electricity for DHW heating and the load was measured for only one of these homes.

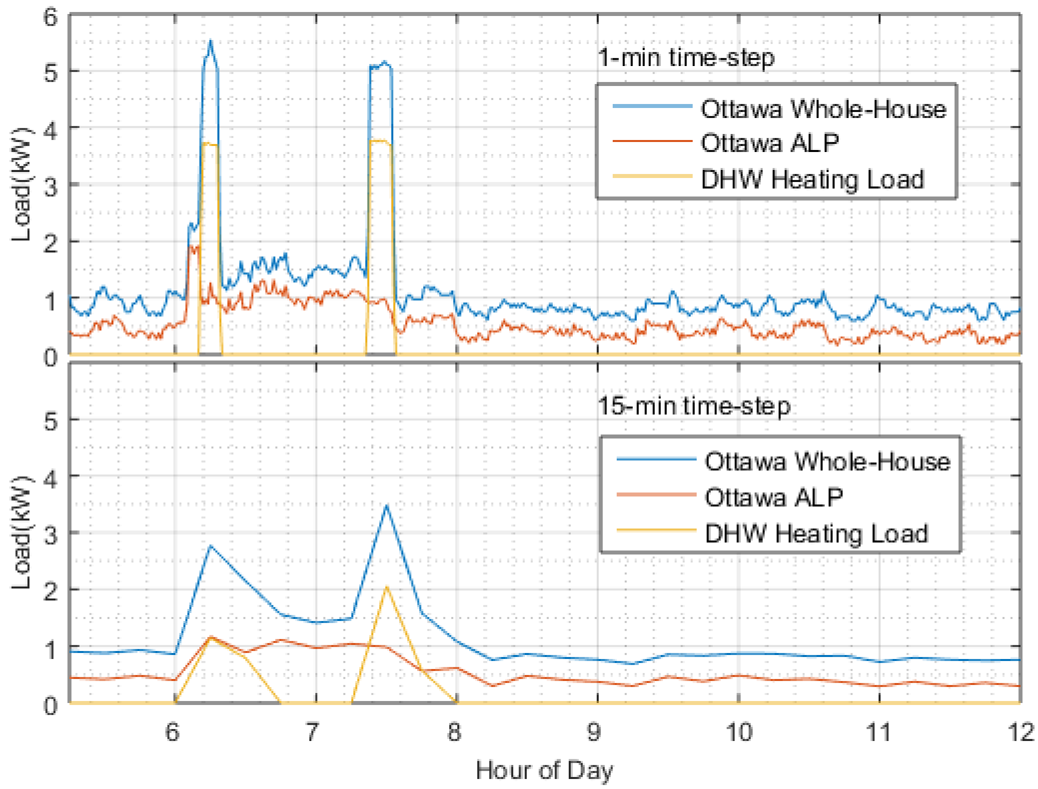

Figure 3.8 DHW, ALP and whole-house load profile 1-minute and 15-minute time-step comparison for one house of the Ottawa dataset

From the upper plot in Figure 3.8, it is shown that when the DHW heater electric element is engaged, there is approximately a 300% increase in the ALP load. The DHW electric element is usually engaged at some point during a time-step interval and due to the averaging effect during this interval, the first load measurement is usually less than the full electric element magnitude. The element will then usually run for multiple minutes and so the subsequent measurements will be at the full electric element draw magnitude until the last measurement, which will also be effected by averaging. At a 15-minute time-step, these loads are usually unevenly spread over one or two 15-minute time-step intervals and the magnitudes of most measurements are reduced significantly. The heating element runtime statistics for the entire year are shown in Table 3.3. A heating event is considered to be any continuous series of non-zero DHW power measurements.

This is demonstrated in the upper plot of Figure 3.8. The plot shows two heating events, where the measured power on the DHW circuit was greater than zero: the first occurs between 6h and 7h and the second between 7h and 8h. Runtime is the length of each heating event in minutes.

Table 3.3 DHW electric element runtime statistics for one house of the Ottawa dataset

Statistic	DHW electric element runtime per heating event (minutes)
Mean	12
Median	10
Maximum	139
Minimum	1
5th Percentile	8
20th Percentile	9
80th Percentile	13
95th Percentile	23

From Table 3.3, the mean element runtime is less than one 15-minute time-step. To be able to identify the DHW load magnitude from a whole-house profile, the element runtime must span 3 or more time-step intervals so that the increase in load could consistently reach the full electric element load magnitude. It might be possible to identify the majority of DHW water heating loads with 1-minute time-step data, but this is not possible with 15-minute time-step data.

To further investigate the 'dampening' effect of the 1-minute to 15-minute time-step increase, a histogram of load measurements for the DHW profile at both 1-minute and 15-minute time-steps is shown in Figure 3.9.

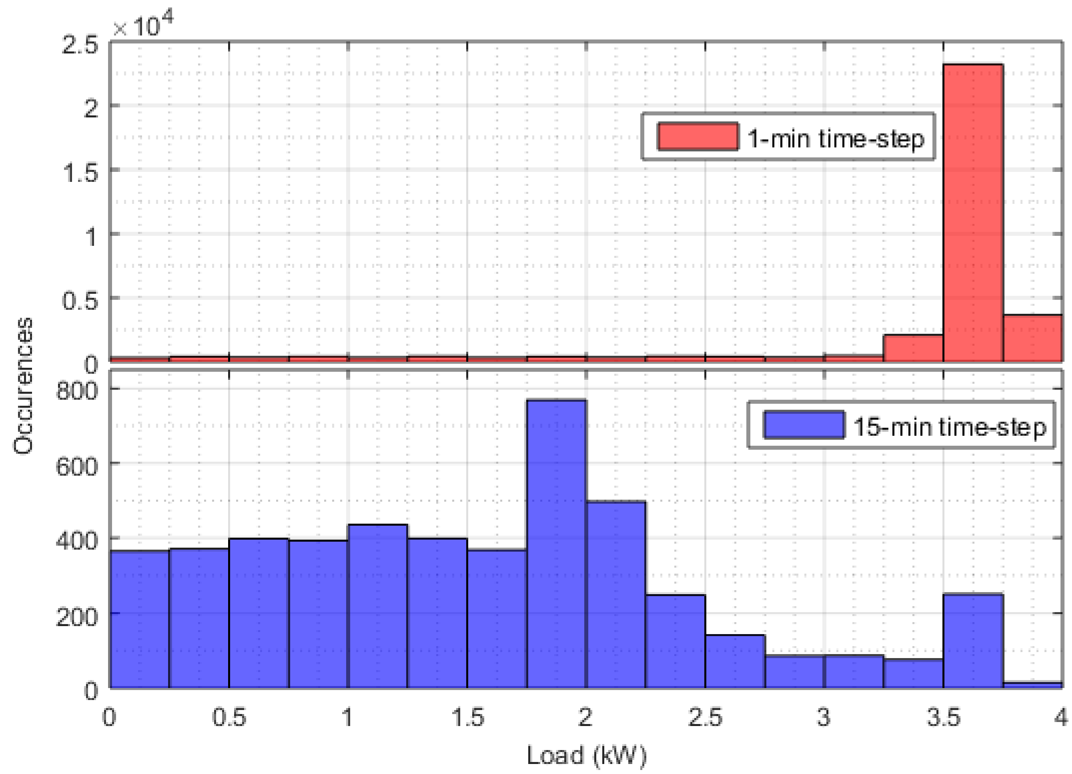

Figure 3.9 Histograms of DHW load measurements at 1-minute and 15-minute time-steps for one house of the Ottawa dataset

The upper histogram in Figure 3.9 indicates that at a 1-minute time-step, the overwhelming majority of the measurements are at the full electric element load magnitude of between 3.5 kW and 4 kW. At a 15-minute time-step, the measurements appear to be spread out from much more evenly spread between zero the full load magnitude. However, the highest occurrences of resulting measurements occur at between 1.75 kW and 2.25 kW which is approximately 50% of the full load. An hourly analysis of the DHW load profile reveals that overnight loads over 1.75 kW do occur, since a DHW heater will operate even during periods of little or no DHW consumption due to heat loss through the tank envelope.

The next step in the analysis assumes that other large appliance loads over 1.75 kW will not often occur overnight in households where the occupants follow a typical schedule of awake during daytime and asleep during nighttime. So the time-step load changes (increases or decreases from one time-step to the next) are examined. Histograms of time-step changes for the Ottawa ALP and ALP + DHW profiles for one house are shown in Figure 3.10.

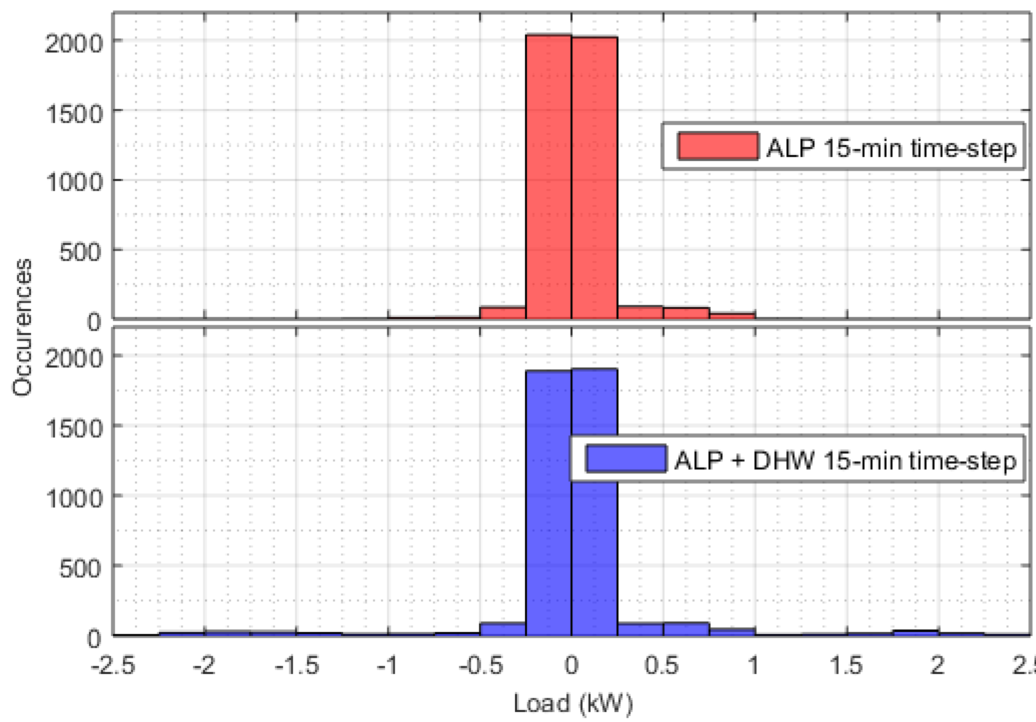

Figure 3.10 Histograms of time-step load changes between 2h and 4h for the ALP and ALP + DHW profiles for one house of the Ottawa dataset

From Figure 3.10, it is shown that overnight time-step load changes below -1 kW or above 1 kW do not occur in the ALP profile, but do occur in the ALP + DHW profile. The ALP + DHW profile showed 145 occurrences of load changes (both in positive and negative directions) over 1.75 kW. The same examination of the 22 Ottawa ALP profiles showed similar results and only one had more than 6 time-step changes over 1.75 kW between 2h and 4h.

Based on these observations, all homes from the Nova Scotia dataset which showed 13 or fewer annual time-step changes over 1.75 kW between the hours of 2h and 4h were assumed to be homes which do not rely on electric DHW heating. A total of 29 homes were selected from set of 41 non-electrically space heating/cooled homes. For one of these homes, only the first two of three years were used, since a jump from 5 to 31 overnight high time-step changes occurred in the third year of measurement, suggesting that an electric DHW heater may have been installed during this year.

This method may not always provide accurate results because ‘outlier’ homes which utilize large appliances overnight may be excluded by this selection process. Furthermore, homes which engage ‘smart’ appliances that are capable of turning on or off overnight may also be excluded using this method.

ALP loads that behave similarly to the DHW load might be also removed by this method. Examples might be other water heating loads such as pools and hot tubs. In their survey of ALP loads in Canadian homes, Parekh et al. (2012) found a 17% penetration of ‘atypical loads’ which include pool and hot tubs loads as well as other recreational loads such as saunas, treadmills, spa pumps, and heated driveways. It should be noted that two houses of the Carleton dataset have hot tubs yet their ALP loads did not demonstrate high nighttime time-step load changes. The exclusion of water heating loads such as these from the ALP dataset may be favourable to building simulators, who might prefer to model those components separately.

3.4.4 Annual ALP Profiles for Building Simulation

Using the above methods, a total of 45 profiles from the Nova Scotia dataset were selected to be non electrically space heated and from these, 41 homes were selected to be non space cooled. Then, the DHW selection method found that 29 of these homes do not rely on electric DHW heating. Some of these ALP profiles include up to three years' worth of data so that in total, there are 62 unique annual ALP profiles. The homes came from two categories of the Nova Scotia dataset, AEH and NEH, demonstrating the importance of re-evaluating meta-data each few years. Although each profile is unique, users should be aware that multiple profiles come from a single house and that this may limit the diversity of the dataset.

It was important to ensure that all profiles aligned temporally so that they all represented one non-leap year (365 days) and began on the same day of the week. For the 2012 year which was a leap year, the last day of measurement in the year was removed as opposed to the data from February 29th. To maintain continuity across all annual ALP profiles, they were shifted to match a year where the first day of measurement fell on a Monday (e.g. 2007). While some 'fixed' holidays such as July 1st (Canada Day) and December 24th (Christmas Eve) were misplaced and wouldn't align across the entire dataset, the weekdays and weekend days remained aligned and other holidays which are regularly shifted to fall on a Friday or Monday would likely still be aligned. Also, since the profiles were circularly shifted and the number of days in a week (7) is not a factor of the total number of days in one year (365), up to two days at the end of the year may not represent the correct day of the week of the measurement.

For further comparison between the two datasets, the Carleton dataset was also adjusted to become a January through December profile. A similar problem occurred where the Carleton measurements began in one year and ended in the next. In order to keep the correct day of the week associated with each measurement, the data was circularly shifted as necessary so that the first day of the annual ALP profile lands on a Monday.

3.5 Profile Comparisons

To affirm the above methods, this section compares the profile characteristics of the two datasets. Temporal variations, load magnitude probability, load fluctuation, peak loads and profile diversity of the Nova Scotia and Ottawa datasets are examined and compared.

3.5.1 Temporal Variations and Statistical Comparison

As identified in the methodology section of this Chapter, ALP loads have been shown to vary temporally on several scales. Thus, annual, weekly, daily and hourly variations are explored in this section.

3.5.1.1 Annual

The identification of homes with electric space conditioning is largely dependent upon annual trends in household and ALP loads (see Sections 3.4.1 and 3.4.2) and therefore it is useful to examine the annual trends of the selected Nova Scotia profiles to affirm the methods used. The average monthly loads of the selected ALP Nova Scotia profiles and of the Ottawa the ALP profiles are shown in Figure 3.11.

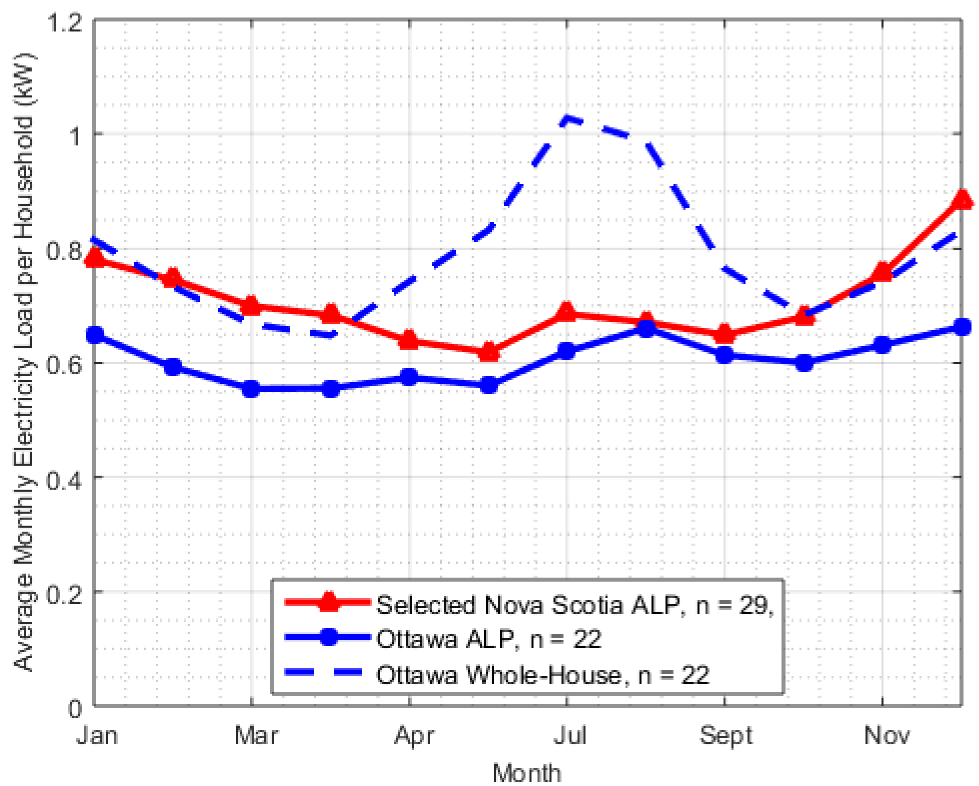

Figure 3.11 Monthly average load profile comparison of Ottawa profiles and selected Nova Scotian profiles

From Figure 3.11, the average seasonal variation of the selected Nova Scotian homes is approximately 0.2 kW. External temperature has an influence on the load (R = -0.69) and this could be partially due to the use of fans/pumps in homes during the heating season, or simply the longer runtime of lighting during winter. The Nova Scotia load is very close to the Ottawa load during the summer months but there is a greater difference of up to 25% which occurs during the winter months. This difference is assumed to be partially due to heating system fan or pump loads but may also be on account of longer lighting runtime in Nova Scotia during the fall and winter months, which is known for overcast and foggy weather.

3.5.1.2 Weekly

ALP loads may also be subject to weekly patterns due to occupant behavior associated with weekdays (common workdays) and weekends (common day off work). The average daily ALP loads throughout a week are shown in Figure 3.12 (note the expanded y-axis scale to accentuate the daily differences).

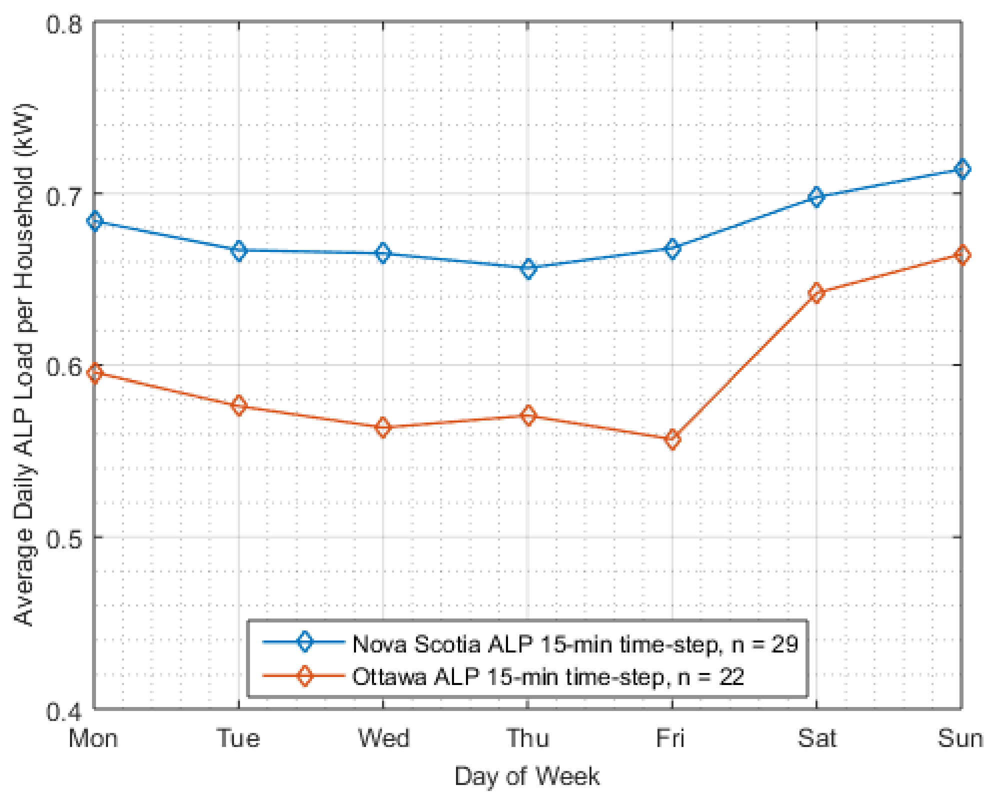

Figure 3.12 Weekly variations in ALP load for the Nova Scotia and Ottawa ALP datasets

From Figure 3.12, both datasets follow a very similar weekly pattern. ALP loads do not vary greatly throughout the week, but a slight peak occurs on the weekend (Saturday and Sunday), likely due to an increased presence of occupants at home during days off work. The differences between average Nova Scotia and Ottawa ALP loads are slightly concentrated during mid-week and the difference diminishes over the weekend. For the Nova Scotia dataset, the average load is approximately 9% higher on weekends than mid-week. For the Ottawa dataset, the average load is approximately 18% higher on weekends than mid-week.

3.5.1.3 Daily

Daily load characteristics from the Nova Scotia and Ottawa datasets are also comparable in magnitude and usage characteristics. Statistics of average daily load per household are shown in Table 3.4.

Table 3.4 Statistical summary of the average daily electricity consumption per household for two datasets

Statistic	Nova Scotia ALP Selected, n = 29 (kWh /day)	Ottawa ALP, n = 22 (kWh /day)
Mean	16.3	14.3
Median	16.8	12.6
Maximum	33.6	30.1
Minimum	3.9	5.9
5th Percentile	4.4	6.3
20th Percentile	10.3	8.5
80th Percentile	20.3	20.5
95th Percentile	28.6	28.3

From Table 3.4, the selected Nova Scotia ALP homes consume 14% more electricity on average than the Ottawa ALP households. These results reflect NRCan (2014a) estimates which suggest that appliance and lighting loads in Nova Scotia are 20% greater than in Ontario. The values in Table 3.4 also compare well with the result of a national survey of ALP loads conducted in 2011 and 2012 by Natural Resources Canada (Parekh et al. 2012) that estimates an average ALP load of 19 kWh per day per household which is 17% higher than the mean Nova Scotia ALP value and 33% percent higher than the mean Ottawa ALP value. However, in the survey, ‘supplementary’ space conditioning loads such as portable heater loads were included in the ALP load.

Daily average ALP loads such as those presented in Table 3.4 can be applied in building simulation tools which produce low resolution energy estimates. Hot2000 is a widely used whole-house building simulation tool developed by Natural Resources Canada (CETC 2016a). The default ALP load assumption applied by this software is 19.5 kWh per day, which is 20% higher than the mean daily Nova Scotia ALP value in Table 3.4 and 36% higher than the mean daily Ottawa ALP value.

3.5.1.4 Hourly

The average hourly ALP load for both datasets is shown in Figure 3.13.

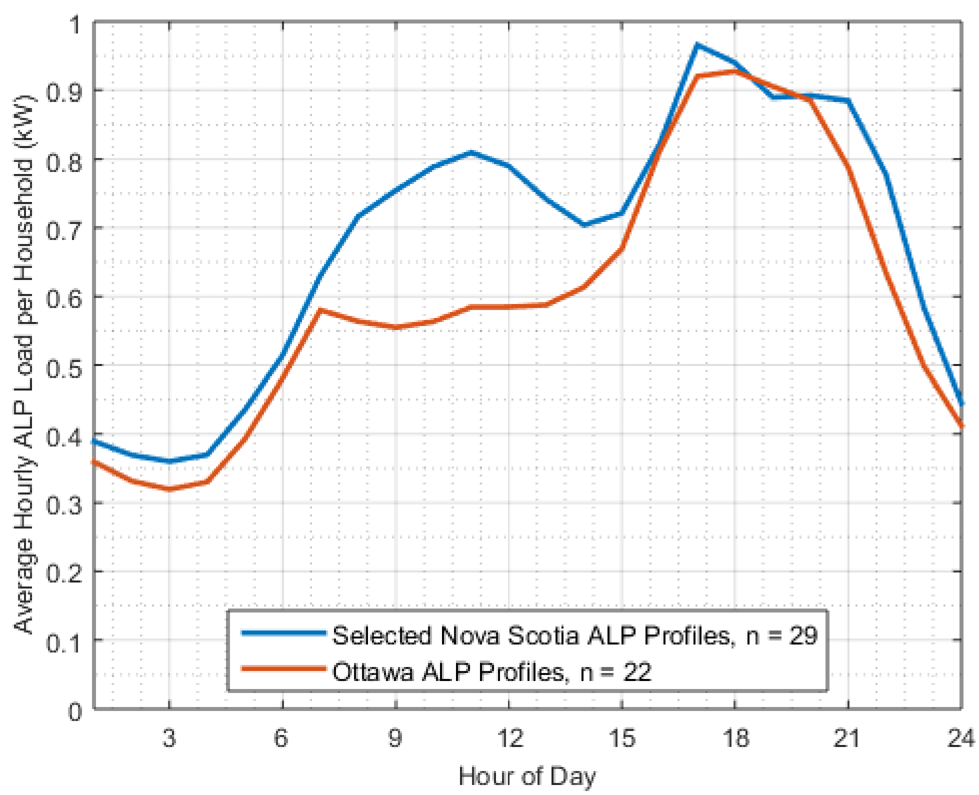

Figure 3.13 Average hourly ALP load for selected Nova Scotia ALP profiles and Ottawa ALP profiles

From Figure 3.13, the average hourly ALP loads of the two datasets are remarkably similar throughout the evening and nighttime periods. However, for the Ottawa dataset, the average hourly ALP load remains relatively constant between approximately 7h and 13 h while for the Nova Scotia dataset, the average ALP load increases throughout the morning until peaking at approximately noon and decreasing again before an evening increase. While the Ottawa load is only marginally less than the Nova Scotia load for most of the day (within 0.1 kW), a larger difference occurs during the morning and midday period. This difference is not easily explained, but may suggest that daytime occupancy of households in Nova Scotia is greater than in Ottawa, although, the proportion of dual-earning families with a least one child under 16 years of age is approximately the same between the two regions (Atlantic Canada: 69.3%, Ontario: 68.2%; Statistics Canada 2015). The limited size and therefore unrepresentativeness of the datasets leaves this question unanswered.

3.5.2 Load Probability Comparison

The magnitude of individual draws occurring in a household may be of interest to building simulators. Two households that consume a similar amount of electricity have very different load patterns and these may cause a new technology to perform very differently between households. For example, for an off-grid solar photovoltaic system with battery storage, the sizing of system components will depend on the magnitude of loads. To ensure that the load magnitudes of the selected Nova Scotia ALP profiles are comparable to the Ottawa ALP profiles, load probability curves are generated for houses with comparable consumption levels. First, the 1-minute time-step Ottawa ALP data was down-sampled to 15-minute time-steps to align with the Nova Scotia dataset time-step. Houses with similar annual consumption levels from each dataset were paired together and a load probability curve at 100 W bin sizes was generated for each pair. Houses were selected to span a range of consumption levels. These are shown in Figure 3.14.

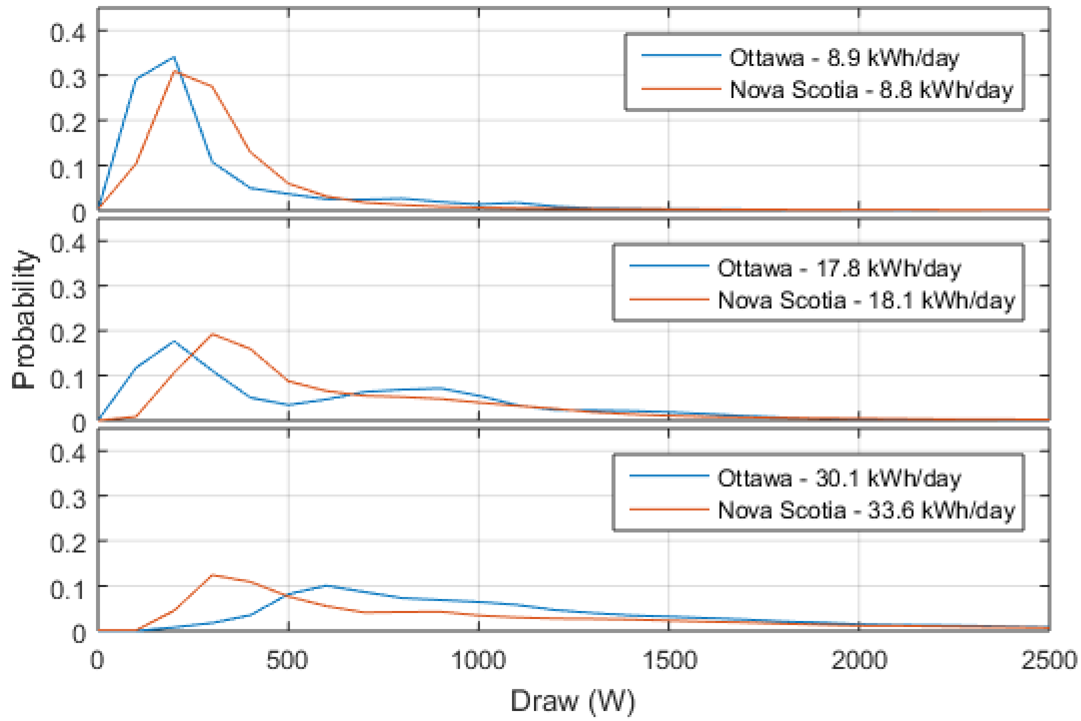

Figure 3.14 Load probability curve comparison for similar houses across the Nova Scotia and Ottawa ALP datasets

The plots in Figure 3.14 show that the probability of load occurrences between similar houses from each dataset are similar in nature. Although no two curves are expected to be identical, the load curves shown are similar in shape magnitude of draws.

3.5.3 Load Fluctuation Comparisons

While the load probability may vary greatly from household to household depending on appliance and lighting counts, the time-step load changes may be more similar across households because appliances and lights will be similar in load magnitude and a load change will represent specific ALP loads turning 'on' or 'off'. While over a 15-minute time-step the actual magnitude of load change will not be well represented (as was shown with regard to DHW heating loads in Section 3.4.3), it is still worth comparing the time-step load changes between the two datasets. For this comparison, the Ottawa dataset is down-sampled to 15-minute time-steps by averaging the load during each 15-minute interval, and the probability of time-step load changes over several ranges is shown in Figure 3.15. The ranges were selected to represent several categories of small through large appliances. For example, plug-loads and lighting loads may generally be between 10-100W while appliances such as refrigerators may be in the 100-1000W category. Large appliance loads such as hair dryers, toasters or ovens would fall in the over 1000W, though some of these may be reduced to a lower category due to sub-time-step run periods.

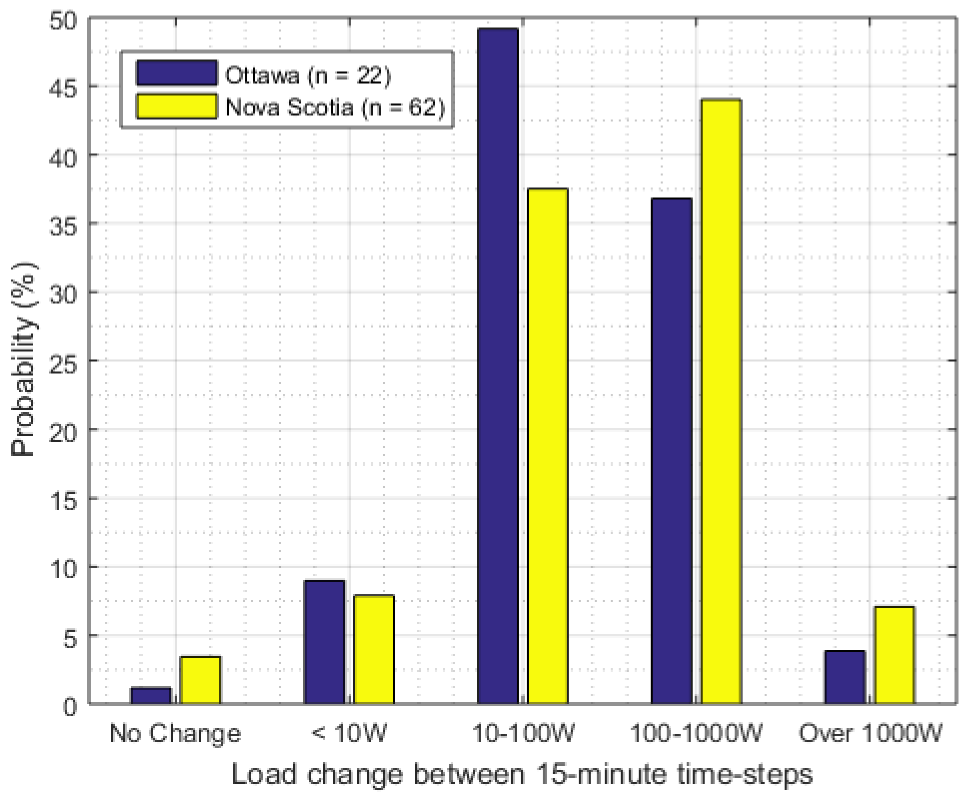

Figure 3.15 Time-step load change probability for the Ottawa and Nova Scotia datasets

From Figure 3.15, the load changes between the two datasets generally fluctuate similarly, with only slight discrepancies in the two high probability categories (10-100W and 100-1000W).

3.5.4 Peak Load Comparisons

To adequately evaluate the power demand reduction potential of building technologies it is important to capture the time-step changes in ALP load in building simulation. Appropriate time-step resolution of profiles may vary from case to case. For example, Naspolini and Rüther (2016) found that 15-minute time-step resolution is inadequate when evaluating the demand reduction potential of solar DHW systems in Brazilian communities where instantaneous electric showerhead water heaters contribute significantly to utility peak demand. The problem arises because the average length of a shower is less than 15 minutes. This was also demonstrated in a Canadian context by Figure 3.9 in Section 3.4.3 of this Chapter, which shows a decrease in peak load magnitude of an electric DHW heater when using 15-minute vs. 1-minute time-step resolution data, also because DHW heater electric element runtimes are on average less than 15 minutes.

To further demonstrate this effect and to compare the selected Nova Scotia ALP profiles to the Ottawa ALP profiles, the annual peak loads are plotted against the mean loads for each profile of the Ottawa dataset at 1-minute and the Nova Scotia dataset at 15-minute time-steps in Figure 3.16. Furthermore, the Ottawa dataset has been down-sample to a 15-minute time-step and this has been included in Figure 3.3 as well. Note that for the Nova Scotia dataset, each of the selected 62 annual ALP profiles are considered separately and therefore up to three datapoints may belong to one house. The statistics of the 'peak-to-mean' ratios associated with Figure 3.16 are then shown in Table 3.5.

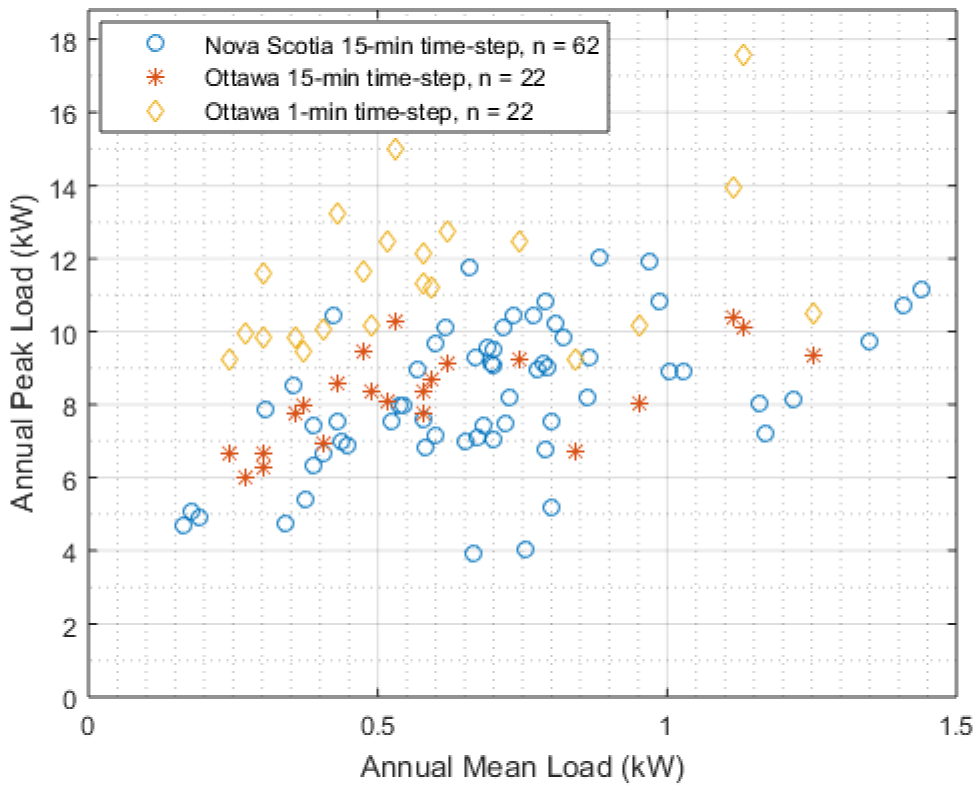

Figure 3.16 Annual peak load vs. annual mean load for annual ALP profiles from the Nova Scotia and Ottawa datasets

Table 3.5 Range of peak-to- mean ratios for both annual ALP datasets

Dataset	Time-step (minutes)	Peak-to-Mean Ratios		
		Mean	Min	Max
Nova Scotia	15	13.5	5.4	28.5
Ottawa	15	16.2	7.5	27.3
Ottawa	1	23.0	8.4	38.5

From Figure 3.16 and Table 3.5, both datasets at 15-minute time-steps have a similar range and average peak-to-mean ratio, suggesting similar load characteristics between the Ottawa ALP load profiles and the selected Nova Scotia ALP profiles. The Ottawa 1-minute time-step profiles, however, demonstrate a much higher 'peak-to-mean' ratio, which is on average 40% higher than the peak to mean ratio of the same profiles at 15-minute time-steps.

The higher 'peak-to-mean' ratios associated with shorter time-steps highlight the need for using a variety of profiles for community modeling because the peak loads will be magnified if a profile is used to represent multiple houses in a community. The same demonstration is conducted on hypothetical community ALP loads by summing all of the loads of each dataset. The corresponding 'peak-to-mean' ratios are shown in Table 3.6.

Table 3.6 Peak-to-mean ALP load ratios for community scenarios

Dataset	Time-step (minutes)	Peak-to-Mean Ratios
Ottawa (n = 22)	1	4.0
Ottawa (n = 22)	15	3.3
Nova Scotia (n = 62)	15	2.7
Nova Scotia + Ottawa (n = 84)	15	2.7

From Table 3.6, the 'peak-to-mean' ratio of a community decreases as the time-step is increased and as the community grows in size. Hypothetically, this ratio will decrease to a limit so that over an entire region, the 'peak-to-mean' ratio is predictable at any time-step above 1-minute. It is expected that beyond some community size, the 'peak-to-mean' ratios of the community ALP load will not decrease below a limit and that the load will follow a fairly consistent pattern every day. An example of these community profiles are shown for one week in the winter and summer in Figure 3.17.

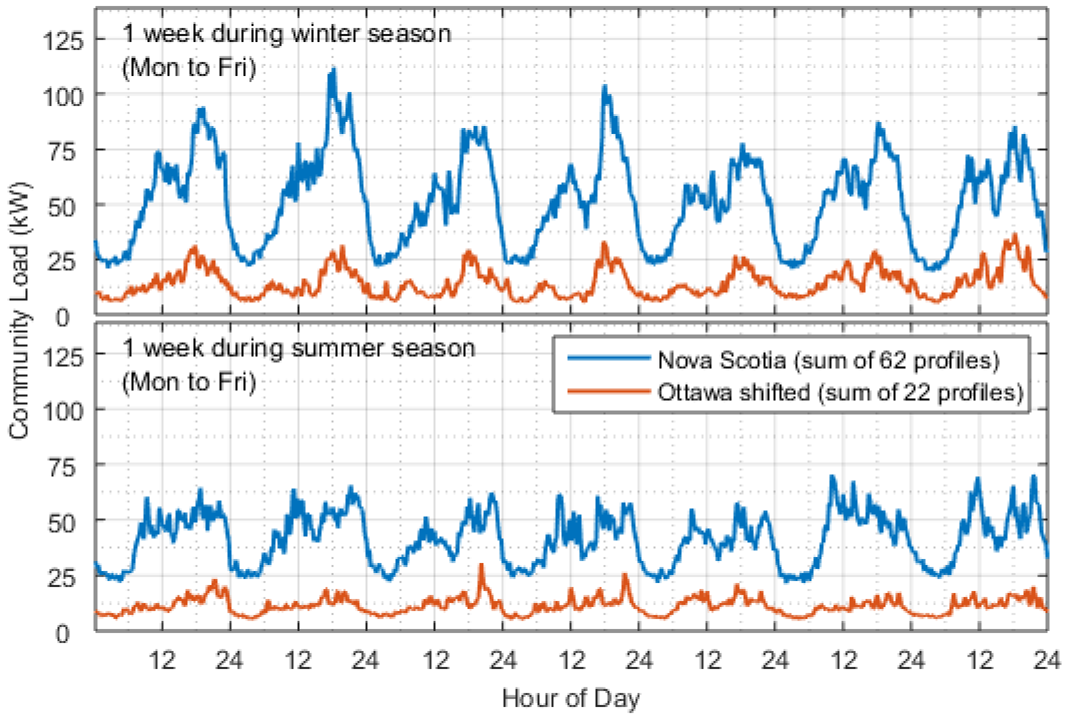

Figure 3.17 Example of Nova Scotia and Ottawa community ALP loads during winter (top) and summer seasons (bottom)

In Figure 3.17, the community ALP loads follow a fairly consistent daily pattern. However, this daily pattern differs between the winter and summer months, showing that the subtle seasonal variations shown in Figure 3.11 manifest themselves in the shape of the hourly profile. In the winter plot, there is a noticeable increase in ALP load during the evening hours while in the summer plot, the ALP load remains relatively constant throughout daytime hours. This difference may be largely due to lighting loads during darker winter months. As a result, the daily peak loads are approximately 25-40% lower on any given day in the winter season than in the summer season. For this reason, it is important to be wary of time-shifting of ALP load profiles to generate additional non-coincident profiles for community simulation.

The findings are quantified by contrasting the peak-to-mean ratios of the various community loads during the winter season (Dec 20 – Mar 20) and the summer season (Jun 20 – Sep 23). The winter and summer 'peak-to-mean' ratios are given in Table 3.7, showing that the peak-to-mean ratios are between 7% and 22% lower during the summer months.

Table 3.7 Seasonal differences in peak-to-mean ALP load ratios for larger community scenarios

Dataset	Time-step (minutes)	Peak-to-Mean Ratios		
		Winter	Summer	% Difference
Ottawa (n = 22)	1	3.6	3.4	7%
Ottawa (n = 22)	15	3.0	2.7	10%
Nova Scotia (n = 62)	15	2.4	1.9	20%
Nova Scotia + Ottawa (n = 84)	15	2.3	1.9	21%

3.5.5 Diversity Factor

Another approach to evaluating diversity of temporal behavior within a dataset is to calculate the diversity factor of the dataset, as outlined by Kersting (2002). This method first calculates the 'maximum non-coincident' load of the community (sum of individual household peak loads) which is the load that would occur if the maximum load for each household occurred simultaneously. Next, the 'maximum diversified' load of the community (community peak load) is calculated. The diversity factor is ratio of these two values.

The diversity factor will generally increase with the size of a community, but eventually will level off when the community reaches a certain size. This is reflected in Figure 3.18 where the diversity factors are shown for the Nova Scotia and Ottawa ALP datasets with an increasing community size.

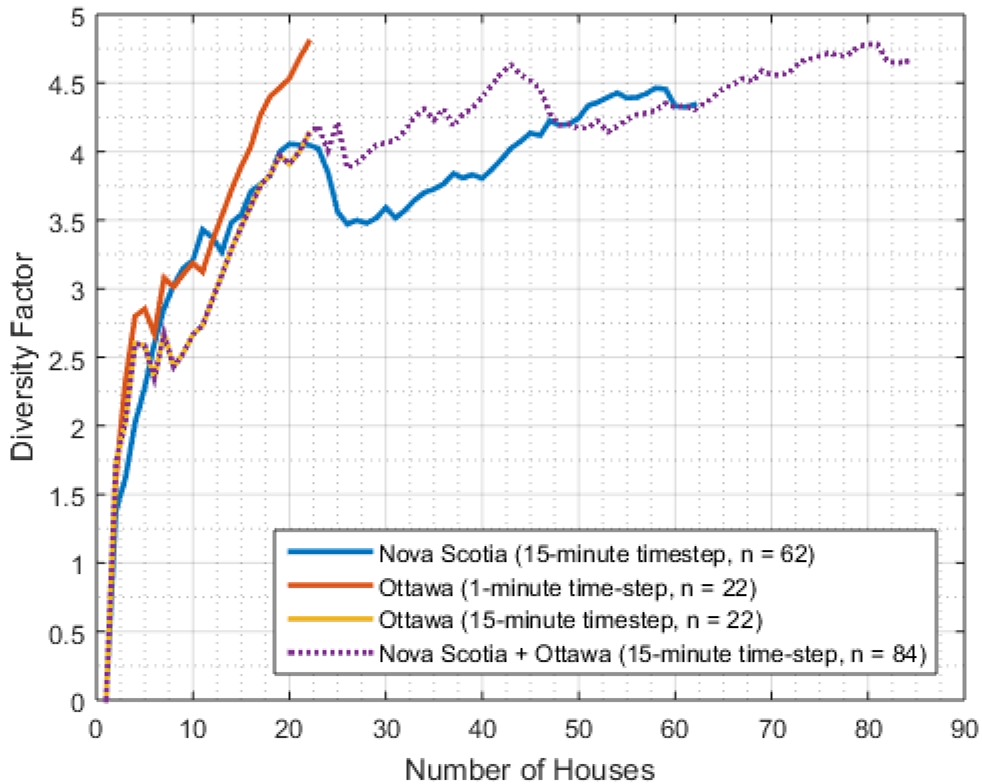

Figure 3.18 ALP load diversity factors with increasing community size at various time-steps

From Figure 3.18, the diversity factors for each community initially increase rapidly and for the Ottawa ALP load profiles at both time-steps the diversity factor does not plateau. For the Nova Scotia and combined (Nova Scotia + Ottawa) datasets, the diversity factor begins to level off at about 21 houses.

There is a sharp decrease in the diversity factor for the Nova Scotia ALP community that occurs between 21 and 25 houses suggesting that maximum non-coincident and diversified loads of the community are increasing at the same rate as each new house ALP profile is added to the community. An investigation showed that the profiles added at this point do not belong to the same household, so it is mere coincidence that the maximum non-coincident and diversified loads of these households are equivalent.

The diversity factor of a community is useful to distribution system modelers because the maximum diversified load of a community can be predicted by computing the maximum non-coincident demand from several community profiles and dividing by the diversity factor.

Furthermore, the diversity factor can provide a means to compare the diversity of various occupant load profile datasets. Table 3.8 shows the diversity factors for the Nova Scotia and Ottawa ALP datasets alongside diversity factors for various other measured and synthetic datasets.

Table 3.8 Diversity factors of various datasets

Dataset	Maximum non-coincident load (kW)	Maximum diversified load (kW)	Diversity factor
Ottawa (1-minute time-step, n = 22)	253.7	52.9	4.80
Ottawa (15-minute time-step, n = 22)	180.8	43.8	4.13
Nova Scotia (15-minute time-step, n = 62)	511.3	117.8	4.34
Nova Scotia + Ottawa (15-minute time-step, n = 84)	692.1	148.6	4.66
Synthetic data (Armstrong et al. 2009) (5-minute time-step, n = 9)	79.8	34.4	2.32
Synthetic data (Richardson et al. 2010) (1-minute time-step, n = 22)	260.0	49.6	5.24
Measured data (Richardson et al. 2010) (1-minute time-step, n = 22)	240.8	46.5	5.18

Diversity ratio is affected by time-step and from Table 3.8, the Ottawa 1-minute time-step appear to be more diverse than the same dataset down sampled to 15-minute time-steps. This is because local peaks that occur due to short duration loads and don’t line up across two 1-minute time-step profiles might align when they are averaged out over 15-minute time-steps. So, it is more likely that the for larger time-steps, the maximum diversified load (denominator) higher than it would be at a shorter time-steps relative to the maximum non-coincident load (numerator), resulting in a lower diversity factor.

Also, diversity increases with community size and so the combined Nova Scotia and Ottawa datasets result in a higher diversity factor than for the individual datasets. Meanwhile, the diversity factor of the synthetic dataset generated by Armstrong et al. (2009) is quite low due to the limited number of profiles (n = 9).

As more ALP data becomes available throughout Canada, it would be interesting to compare the diversity factors of various regions, especially if powershifting of large appliances is rolled out on a community scale.

3.6 Data Representativeness

These profiles are intended for community scale simulation and provide a new dataset which encompasses realistic temporal variability between houses and within individual houses. However, the profiles might be used to represent a wider region of homes or a group of homes in different region altogether. This section intends to provide some insight into the representativeness and transferability of this data in the Canadian and North American context.

The datasets provide a total of 62 unique annual ALP profiles (from 29 homes) for the Nova Scotia region and 22 for the Ottawa region. These numbers are not statistically significant to represent either of these regions. Furthermore, the selection process of the Ottawa houses is unknown and may result in a skewed dataset. Additionally, the Nova Scotia ALP loads were selected using a process which may result in the exclusion of non-typical load profiles. In Nova Scotia, there are approximately 260,435 single-detached houses (Statistics Canada 2013b) and in Ottawa there are approximately 226,185 single-detached houses (Statistics Canada 2013c), so a larger number of homes should be sampled for these datasets to be considered representative.

Across Canada there are over 7 million single-detached households (Statistics Canada 2013b), so a statistically representative dataset would need to be larger[9], homes should be sampled evenly throughout Canada. However, while average ALP loads may vary slightly from region to region due to climatic differences (e.g. daylight hours) and demographics (e.g. appliance ownership), it is likely that in each region in North America a variety of ALP user characteristics can be found. It should also be noted that ALP loads will vary throughout time as appliances and lighting are updated and efficiency programs are rolled out in various regions.

Notwithstanding, these datasets are of significance, as there are over 30,000 days worth of data. This provides a variety of load combinations at high temporal resolution spanning all seasons. This is uncommon for building simulators and this dataset could be very useful for simulating technologies in community scenarios.

3.7 Conclusions

This comparison between two datasets of residential load measurements demonstrates the use of seasonal and daily observations to distinguish profiles which rely on electricity for space heating and cooling as well as DHW heating. This method relies on a combination of seasonal and hourly differences (i.e. evening shoulder season vs. evening heating and cooling season) in whole-house electricity consumption to identify homes that rely on space heating and space cooling and overnight occurrences of large electricity loads to identify homes with electric DHW heating. The remaining profiles are presumably largely driven by appliances, lighting, and plug-loads, and may be of particular use to researchers conducting building simulation on community and regional scales, and especially those considering coincident demand of net-zero energy communities.

[9] A dataset representative of 7 million Canadian homes would require 384 houses for a 95% confidence interval with a 5% margin of error.

A major benefit of this method is that it can be applied to much larger datasets to generate additional ALP profiles. With smart metering programs rapidly increasing the installation rate across Canada and internationally, a large number of homes are becoming equipped to measure the whole-house electricity load. Moving forward, this method can be applied to much larger datasets as they become available across Canada, thus inexpensively generating geographically representative datasets of ALP load profiles for building simulation.

The 62 new ALP profiles generated by this research capture a variety of temporal consumption patterns and peak-to-mean ratios and they can be applied in building simulations to analyze electricity demand of entire communities. The following Chapters will focus on their application in both individual household and community scale simulations.

Chapter 4 Building Simulation Application Using Occupant Load Profiles

The annual occupant load profiles described in Chapter 2 (DHW) and Chapter 3 (ALP) are intended to be applied to models within building simulation engines for carrying out time-step evaluations of energy demand (power) and technology performance. This Chapter demonstrates their use with the EnergyPlus simulation tool using existing building energy models. For comparison, simulations are also conducted using two previously developed sets of profiles: 9 ALP and 3 DHW high resolution profiles synthetically developed using probability techniques and a set of appliance specific, low resolution profiles developed by the Pacific Northwest National Laboratory (Taylor et al. 2015). Simulation results between the new annual occupant load profiles and the synthetic occupant load profiles are analyzed and compared. Furthermore, two applications are demonstrated: a technical evaluation of tankless water heaters and an economic evaluation of an alternative electricity tariff.

4.1 Simulation Details

The simulation software applied in this research is EnergyPlus which is widely used by researchers and industry. EnergyPlus is a sub-hourly, whole-building energy simulation software based on fundamental heat balance principles which is used to model energy consumption for heating, cooling, ventilation, lighting, and plus and process loads. It is an integrated simulation software where the building (i.e. zone loads), systems (i.e. air loops) and plants (i.e. hydronic loops) are solved simultaneously with constant time-step feedback to one another. A detailed account of integration methodology and governing equations can be found in the v.8.4.0 EnergyPlus documentation: *Engineering Reference, The Reference to EnergyPlus Calculations* (EnergyPlus 2015).

For this work, the EnergyPlus input files (IDF) files were edited without the use of 3rd party Graphical User Interfaces.

4.1.1 Building Simulation Inputs

Building simulation tools such as EnergyPlus require input data to create a building energy model. Inputs can be categorized into three types of inputs (shown in Figure 4.1): (1) building characteristics which make of the physical description of a building, (2) representative climate datasets[10], (3) occupant loads such as DHW and ALP loads. By using these 'Archetype' models, the building characteristics and climate data input requirements are satisfied and the occupant load profiles can be easily demonstrated.

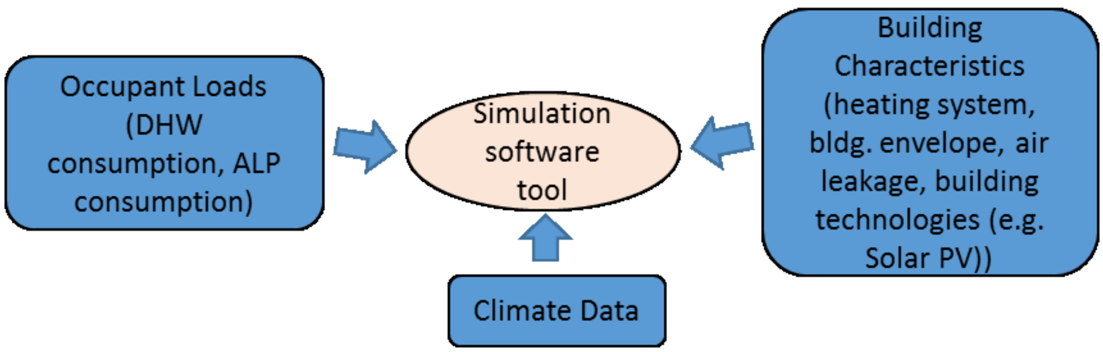

Figure 4.1 Building Simulation Inputs

4.1.2 Archetype Models

To facilitate a quick application of the occupant load profiles, previously existing building energy models were used: the single-family Residential Prototype Building Models were developed by the Pacific Northwest National Laboratory (Taylor et al. 2015), henceforth be referred to as the Archetype Models[11].

[10] Climate datasets are compiled from various sources and are freely available online at the following link: https://energyplus.net/weather

[11] The Archetype Models are available for download at the Department of Energy website at the following link: 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 were 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). Figure 1.1 shows a sketch of an Archetype Model[12] and Table 4.1 lists their characteristics.

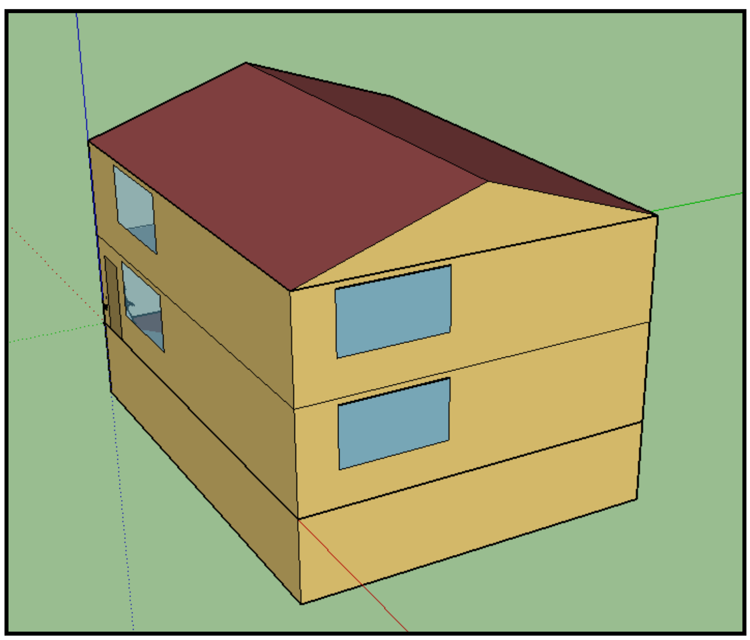

Figure 4.2 Sketch of Archetype Model house (Taylor et al. 2015)

[12] This sketch was obtained using the SketchUp IDF import function. The sketch depicts the single-family Archetype Model for Portland, Maine.

Table 4.1 Archetype model characteristics (adapted from Taylor et al. (2015))

Parameter	Assumption
Conditioned floor area	221 m^2 (plus 110 m^2 of unconditioned basement)
Zone division	Three zones, basement, living area and attic
Footprint and height	5.0 m by 2.0 m, two-story, 0.8 m high ceilings
Area above unconditioned space	110 m^2
Area below roof/ceilings	110 m^2
Perimeter length	14.1 m
Gross exterior wall area	240 m^2
Window area (relative to conditioned floor area)	Fifteen percent equally distributed to the four cardinal directions
Door area	3.9 m^2
Internal gains	25.43 kWh/day
Heating system	22.22 °C setpoint, natural gas furnace, heat pump, or electric resistance furnace
Cooling system	23.88 °C setpoint, central electric air conditioning
Water heating	Mixed 200 L tank, same as fuel used for space heating

In Nova Scotia, the average floor space of single detached homes is 149 m^2; however, the average floor space of homes that were constructed after 1996 is 218 m^2, which is comparable to the heated floor area of the Archetype Models (NRCan 2014a). Several recent studies on solar optimal neighbourhood design have modeled an average heated single detached floor area of 180 m^2 (Hachem et al. 2012, Hachem et al. 2013, Hachem 2015, Hachem 2016), values 20% smaller than the Archetype Models. However, these studies intend to simulate low-energy house designs.

4.1.3 Model and Climate Data Selection

Three of the Archetype Models were selected to represent two variations of electrically heated homes with electric resistance furnaces (ER) and air-sourced central heat pumps (HP) and non-electrically heated homes with natural gas (NG) furnaces. Each house model is of identical construction with an unheated basement and satisfies the 2012

International Energy Conservation Code requirements (ICC 2012). The models were design based on additional energy codes of Portland, Maine, and were chosen because of Portland's proximity to the eastern Canadian border. Climate data for this location is available at 1-hour time-steps.

4.1.4 Occupant Load Profiles

Three sets of occupant load profiles are applied in the simulations in this Chapter.

4.1.4.1 Default Occupant Load Profiles

The existing ALP and DHW profiles within the Archetype Models consist of repeated 24-hour profiles at 1-hour time-steps for individual ALP and DHW end-uses (e.g. interior lighting, clothes washer, misc. plug-loads etc.). These loads profiles have been constructed by the Pacific Northwest National Laboratory (Taylor et al. 2015), drawing from several resources such as Hendron and Engebrecht (2010) and ICC (2012). For individual end-uses such as refrigerators, sinks, and clothes washers, a separate 24-hour profile has been generated for weekdays, weekends, and vacations. For comparison with other ALP profiles, the individual end-use profiles are combined into one ALP profile.

4.1.4.2 Synthetic Occupant Load Profiles

The nine ALP profiles generated by Armstrong et al. (2009) and three DHW consumption profiles generated by Jordan and Vajen (2001a) are high temporal resolution, annual profiles that were compiled for the IEA Energy Conservation in Buildings and Community Systems Programme's Annex 42 which sought to improve the modeling of fuel cell and other cogeneration technologies[13]. This subsection will describe their origin.

[13] They are freely available from the Programme's website at the following link: http://www.ecbcs.org/annexes/annex42.htm.

4.1.4.2.1 Synthetic DHW Profiles

To model DHW demand, Jordan and Vajen (2001a) used a probability approach based on data gathered in Germany and Switzerland (Knight et al. 2007). The model produced a different profile for each day of the year at 1, 6, and 60-minute time-steps and for mean daily consumption levels of 100, 200, 400, and 800 L/day. A method was also developed to superimpose profiles in order to generate new profiles at different increments (i.e. a profile for a mean daily consumption of 300 L could be generated by superimposing 100 L and 200 L profiles). The model assumes four categories of loads: short loads (i.e. washing hands, etc.), medium loads (i.e. dishwasher, baths, and showers). Within each category, assumptions are made for the mean flow rate, load duration, incidences, and the statistical distribution of different flow rates. Days of the week, seasons, and holidays are also considered.

For Annex 42, measured DHW profiles at 5 and 60-minute time-steps from the U.S., Canada and various countries in Europe were compiled and used to calibrate the model created by Jordan and Vajen (2001a). The DHW consumption data used in Annex 42 did not include information on occupancy levels, data collection methods or date of data collection. The DHW consumption levels and patterns from in different regions varied greatly: average daily DHW consumption in North American was over 200 L/day while European consumption was closer to 100 L/day. Using these daily estimates as the basis, the probabilistic model developed by Jordan and Vajen's (2001a) was then employed to generate annual DHW profiles with 100, 200, and 300[14] L/day average consumption at 1-minute time-steps. Then, 5 and 15-minute time-step profiles were created by aggregating the 1-minute time-step profiles over the longer time intervals.

[14] Generated by superimposing the 100 and 200 L/day profiles.

4.1.4.2.2 Synthetic ALP Profiles

Similarly, Armstrong et al. (2009) used a probability approach to generate the nine, 5-minute time-step ALP electricity demand profiles. They were meant to represent 'typical' detached Canadian households at three consumption levels: (1) *low demand* to represent energy conscious family, (2) *medium demand* to represent a regular family in an average detached house, and (3) *high demand* to represent a large family with no interest in energy conservation, living in a large detached house.

Bodies of information were collected from various Canadian sources to create the profiles:

- appliance stock data was required to estimate appliance numbers per household,
- appliance characteristics such electrical draw, cycle duration and cycles per year were required to construct specific appliance run-time events,
- time-of-use probability curves were required to predict occupant actions to control the probability of an event occurring,
- annual consumption estimates were required to develop annual target energy consumption of each appliance.

With this information, eight sub-load profiles were generated: refrigerator, freezer, dishwasher, clothes washer, clothes dryer, range, other appliances and lighting. These were then combined to create whole-house ALP profiles.

A total of nine 5-minute time-step profiles were generated to represent three years at each of the three consumption levels. The characteristics of these profiles are shown in Table 4.2

Table 4.2 Synthetic DHW Profile Characteristics (adapted from Armstrong et al. 2009)

		Average Daily Consumption (kWh/day)	Average Daily Draw (kW)	Maximum Yearly 5-minute Draw (kW)
Low Demand	Year 1	13.1	0.54	8.10
	Year 2	12.8	0.53	7.43
	Year 3	13.3	0.55	6.97
Avg. Demand	Year 1	22.4	0.93	8.81
	Year 2	22.5	0.94	8.31
	Year 3	22.2	0.93	8.76
High Demand	Year 1	35.5	1.48	10.48
	Year 2	36.0	1.50	10.93
	Year 3	35.7	1.49	10.05

For the simulations, each ALP profile was matched with the synthetic DHW profile of the same consumption level (e.g. low demand ALP with 100 L/day DHW) so that there were a total of nine sets of synthetic profiles for building simulation but with each DHW profiles repeated three times.

4.1.4.3 New Measured DHW and ALP Profile Pairing

The annual DHW profiles generated from the Solar City and NGTC measured datasets in Chapter 2 and the annual ALP profiles generated from the Nova Scotia and Ottawa datasets in Chapter 3 were sorted based on lowest to highest average consumption (DHW and ALP separately). Then the DHW and ALP profiles were paired based on their order of consumption so that there were a total of 82 sets of DHW and ALP profiles.

4.1.4.4 Profile Comparison

The default, synthetic and measured profiles are contrasted in Figure 4.3, where one of each ALP and DHW profile is plotted for a period of one day.

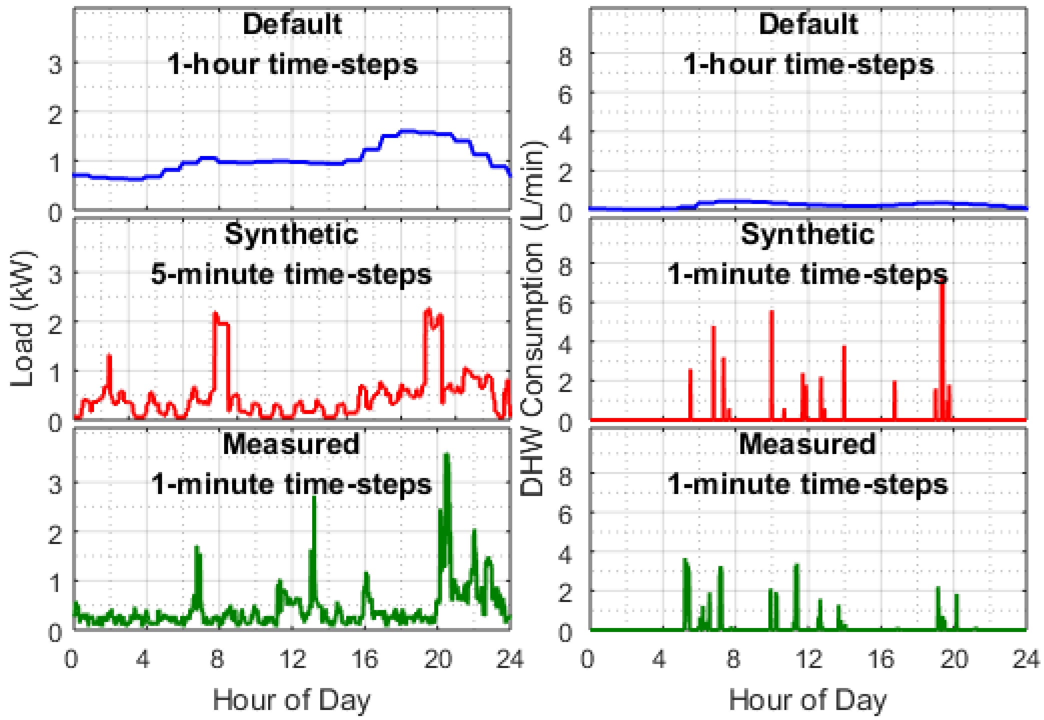

Figure 4.3 Time-step comparisons of three ALP and DHW profile types

From Figure 4.3, the default ALP and DHW profiles are obviously lacking in resolution on account of their 1-hour time-steps. This has the effect of 'smoothing' the profile so that peaks and valleys are no longer visible. Higher resolution synthetic and measured ALP and DHW profiles behave similarly.

4.1.5 Simulation Time-steps

Simulations are conducted at various time-steps in order to best capture the potential of the various occupant load profiles:

- 82 models with measured occupant load profiles were conducted at 15-minute time-steps (Ottawa and Nova Scotia ALP profiles),

- 20 models with measured occupant load profiles were conducted at 1-minute time-steps (Ottawa ALP profiles only). These models are a subset of the 82 models previously generated,

- 9 models with synthetic occupant load profiles were conducted at 5-minute time-steps to match the synthetic ALP profiles,

- 1 model with default occupant load profiles were conducted at 15-minute time-steps which was the default for the Archetype Models despite hourly occupant load profiles.

4.1.6 Simulation of Heating and Cooling System

EnergyPlus models heating and cooling loads with ideal control rather than hysteresis control associated with thermostat setpoints which would usually be found in households. The difference between the two control strategies is demonstrated in Figure 4.4 with a hypothetical example of a single zone system with a single heating coil.

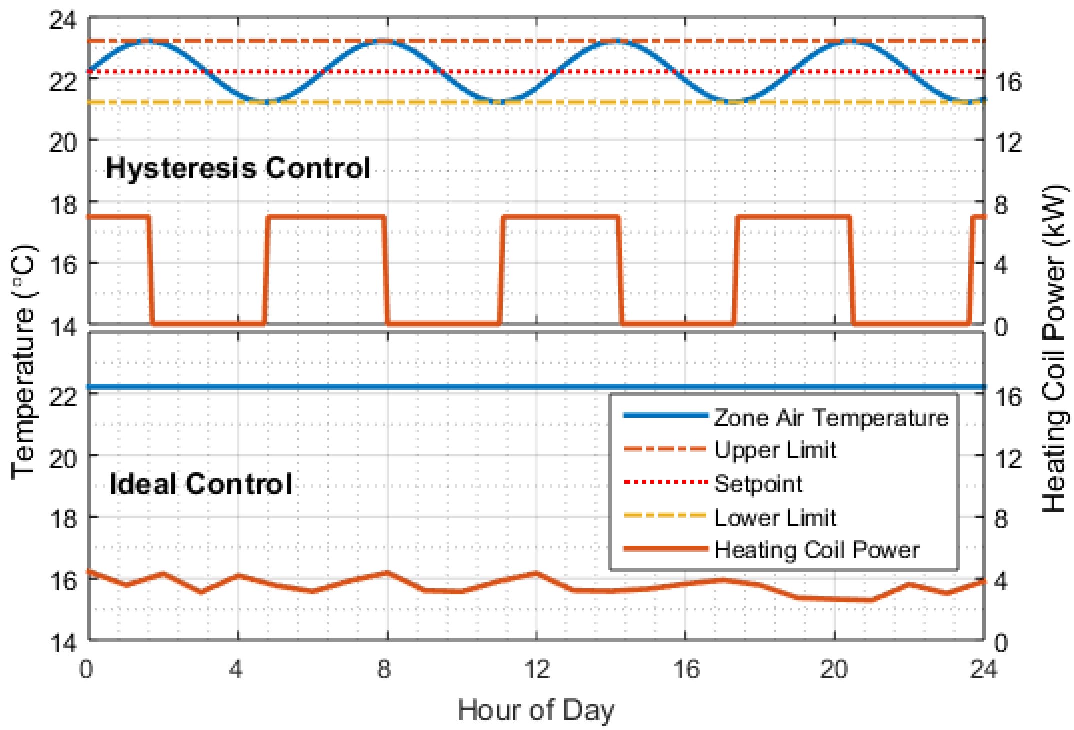

Figure 4.4 Hypothetical example of hysteresis and ideal control

Hysteresis control is shown in the upper plot of Figure 4.4 where the heating coil cycles on when zone temperature falls to a lower limit and remains on until the zone air temperature has reached an upper limit. This cycle repeats itself and the zone air temperature will hover around the zone 'setpoint' without ever settling on it.

Ideal control is shown in the lower plot where the heating coil power is always at 'part load', following the zone heating load so that the zone air temperature will constantly meet the setpoint. This method may produce accurate results for simulations at longer time-steps where the coils may cycle on and off within a time-step and a part load can closely match the real average load from the coil over the time-step. However, where a cycle may span several shorter time-steps (1 to 15-minutes), the heating coil may be on or off during the entire time-step and a part load would not match a realistic load.

For this research, the heating and cooling of the Archetype Models is modeled using ideal control for a single zone which may provide a good approximation of a building with several zones heated by separate coils or a single heating system with variable speed or multi-stage capabilities because the whole-building heating or cooling load will step up and down as coils are switched on or off.

4.2 Simulation Results Analysis

In this section, two output variables generated from the EnergyPlus building simulation tool are analyzed:

- Whole-house electricity load - this is the total electric demand power the whole building ALP and HVAC electric demands averaged over the time-step

- Water heater electric power – this is the electricity demand for the DHW heater element averaged over the time-step

4.2.1 Average Daily Electricity and Water Consumption

Average daily consumption simulated is shown in Table 4.3 for various categories of consumption using the measured, synthetic and default occupant loads. Note that the ‘whole-house’ categories refer to electricity consumption only.

Table 4.3 Average daily consumption per household applying various occupant load profiles to three heating system types[15]

	Applied Occupant Load Profiles		
	Measured (n = 82)	Synthetic (n = 9)	Default (n = 1)
DHW (L/day)	186	200	315
DHW heating energy (kWh/day)	7.9	8.7	12.3
ALP (kWh/day)	16.1	23.7	24.3
Whole-house (NG) (kWh/day)	21.3	29.7	27.5
Whole-house (ER) (kWh/day)	71.0	77.2	82.7
Whole-house (HP) (kWh/day)	53.3	60.4	67.6

From Table 4.3, the default load profiles result in 70% more DHW consumption, 67% more DHW heating energy, 51% more electricity for ALP loads, and between 17% and 27% more whole-house electricity (HP and ER houses) than the measured profiles. The synthetic profiles result in 8% more DHW consumption, 15% more water heating energy, 47% more electricity for ALP loads, and between 8.7% and 13% more electricity overall for electrically heated homes (HP and ER houses). The whole-house load for NG houses is similar to the ALP load. Based on these findings, the default and synthetic profiles may overestimate consumption levels.

It should be noted that DHW heating energy is not a component of the whole-house NG loads because the DHW heating load is satisfied by natural gas.

4.2.2 Hourly Consumption

Average hourly electrical whole-house consumption for NG and HP houses is shown in Figure 4.5 for both in winter and summer seasons for simulations using the measured, synthetic and default profiles.

[15] Note that the DHW heating category is also included in the whole-house electricity load for ER and HP houses but is not included in the whole house loads for the NG houses which rely on NG for water heating.

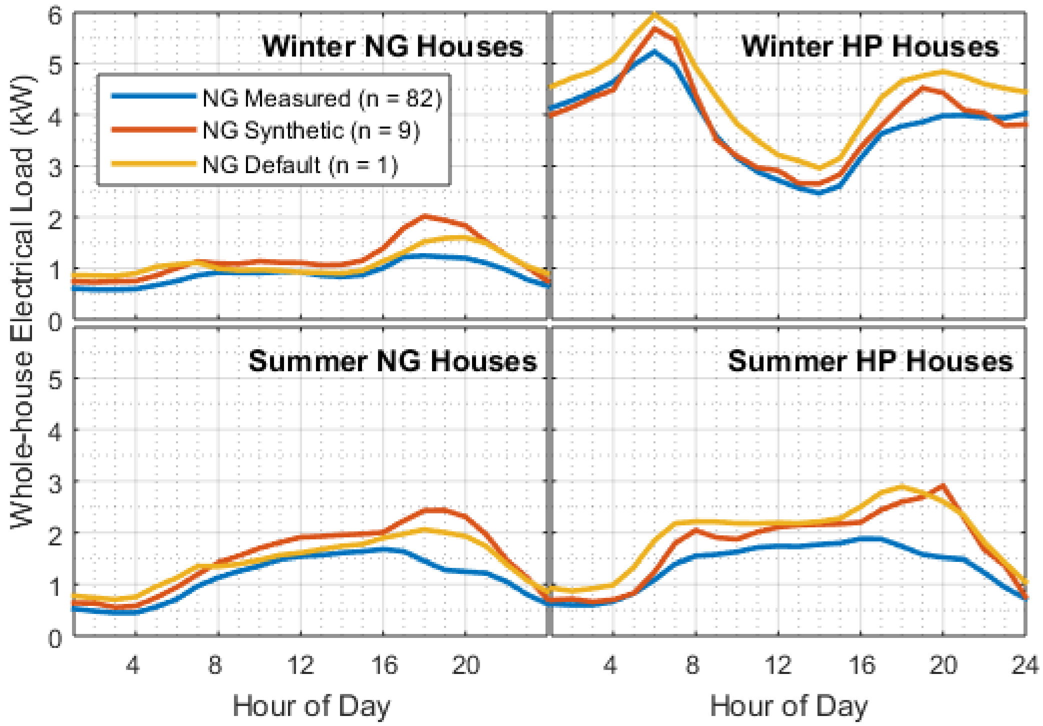

Figure 4.5 Average hourly whole-house electrical consumption for NG and HP houses in winter and summer using measured, synthetic and default occupant load profiles

From Figure 4.5, the hourly whole-house loads generated using the various occupant load datasets follow similar trends but those generated using measured occupant loads are generally lower in magnitude than the others. Furthermore, those generated with synthetic and default occupant load profiles have a small peak between 16h and 21h. If single occupant load profiles were repeated for houses in a larger community, these differences would be magnified. Note, however, that these results are produced by averaging the whole-house loads of many houses (n = 82 for measured, n = 9 for synthetic, n = 1 for default) and individual average hourly whole-house loads vary from house to house, as shown in Figure 4.6.

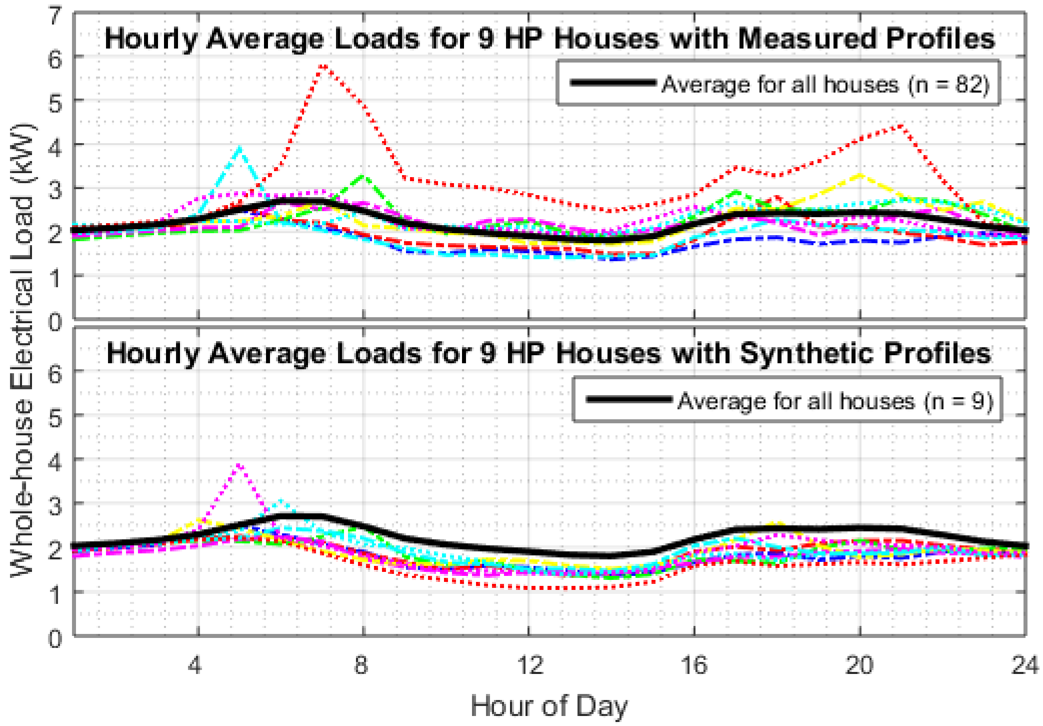

Figure 4.6 Variations in HP whole-house average hourly loads when using measured and synthetic occupant load profiles

The upper and lower plots of Figure 4.6 show the average hourly whole-house electricity load of nine HP houses using measured and synthetic occupant load profiles. In each plot, the thicker, solid black line represents the average hourly whole-house electricity load averaged across the entire datasets. Visual observation suggests that there is more variation in individual profiles when using measured occupant load profiles than when using synthetic. This phenomenon is explored numerically in Figure 4.7 where the correlation coefficients (R^2) of average hourly whole-house loads for individual HP houses to the average across all HP houses is shown when using measured and synthetic occupant load profiles.

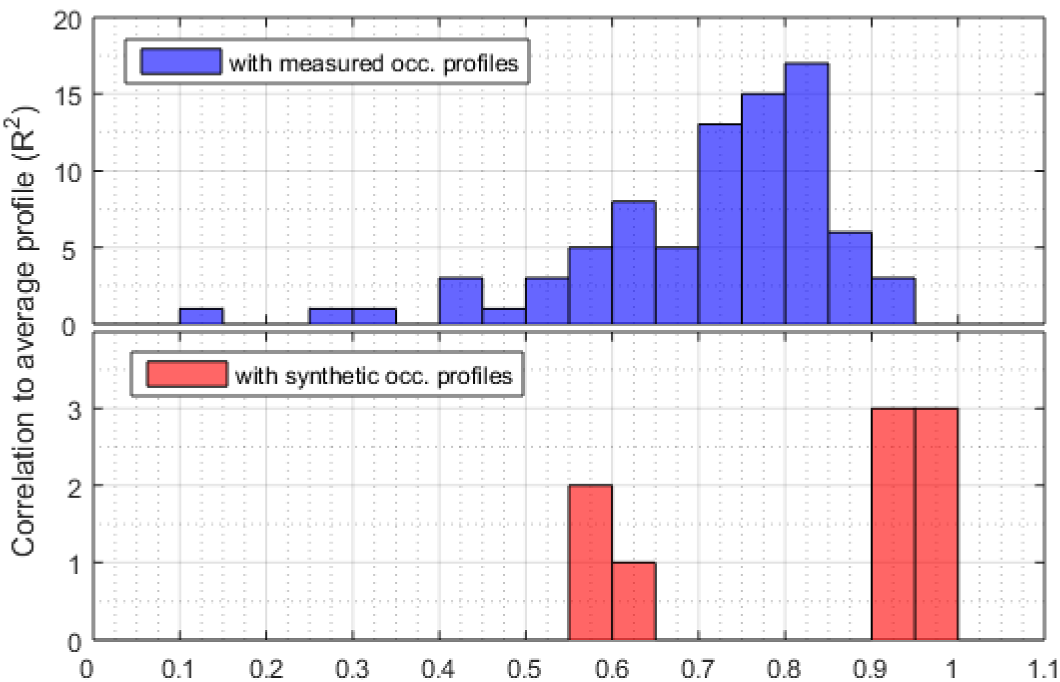

Figure 4.7 Histogram of correlation coefficients (R^2) of average hourly whole-house loads for individual HP houses to the average across all HP houses using measured and synthetic occupant load profiles

From the upper plot in Figure 4.7, there is a range of correlations between individual house average hourly load profiles and the average for the entire dataset. In the lower plot, the variation is much more limited, but centered around approximately the same point. In reality, smaller subsets of communities (~4-8 houses) might all feed into the same polemounted transformer and the larger dataset from the upper plot would provide much more opportunity to explore various combinations of household loads associated with equipment. Such an analysis is carried out in Section 5.4 of this thesis.

4.2.3 Time-step Comparisons

While aggregate consumption analysis on an hourly or daily basis provides an excellent method to analyse overall performance of technologies; electricity demand at high temporal resolution is of interest to energy service providers who face the challenge of sizing distribution equipment and satisfying electricity demand on an on-going basis. The Solar City and NGTC annual DHW profiles and the Ottawa ALP profiles are all at a 1-minute time-step resolution and provide an excellent opportunity to simulate whole-house demand at the same frequency. An example is shown for an ER house in Figure 4.8 where the results are compared at 1, 5, and 15-minute time-steps for January 21st, which is the winter design day for this climate dataset.

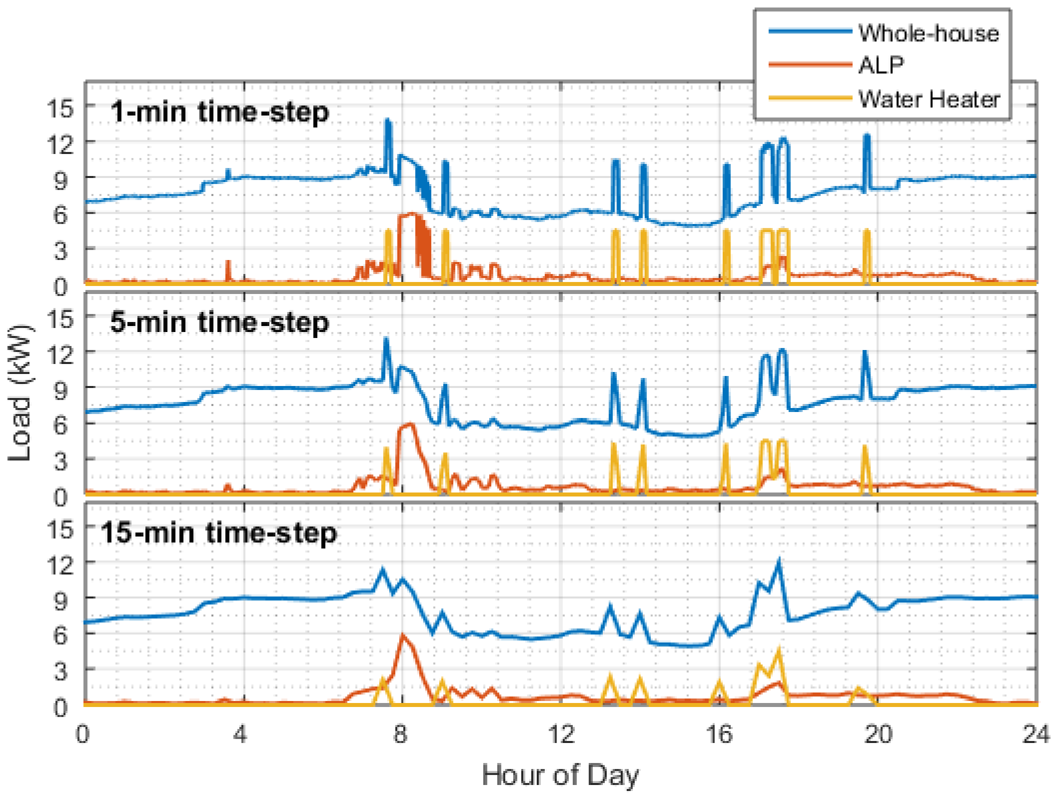

Figure 4.8 Whole-house, ALP and water heater time-step load profiles at 1-minute, 5-minute, and 15-minute time-steps

The upper plot in Figure 4.8 demonstrates that the ALP and water heater loads can have a significant impact on the whole-house load profile. At ~14h a water heater load of ~5 kW is visible in the whole-house load which increases by approximately 52% to 10.5 kW. The ALP load exhibits a similar effect at ~8h, despite it being during the heating season where the average loads in the household are on average 5-9 times higher than the ALP load. In the middle plot at a 5-minute time-step, this effect is still largely apparent and the magnitude of shift in the whole-house load profile is equivalent to that at 1-minute time-step. In the lower plot, at a 15-minute time-step, this effect is reduced for the shorter DHW draws.

Based on these findings, the hourly default occupant load profiles would not be satisfactory for demand modeling while the synthetic profiles at temporal resolutions of 1 to 5-minutes are adequate.

4.3 Technology Application: Electric Tankless Water Heater

Electric tankless water heaters are an option for homeowners that may be attractive to those who lack the necessary space for a larger tank water heater and prefer enhanced operating efficiency compared to a tank water heater. A tankless and tank water heater are shown in Figure 4.9 for comparison.

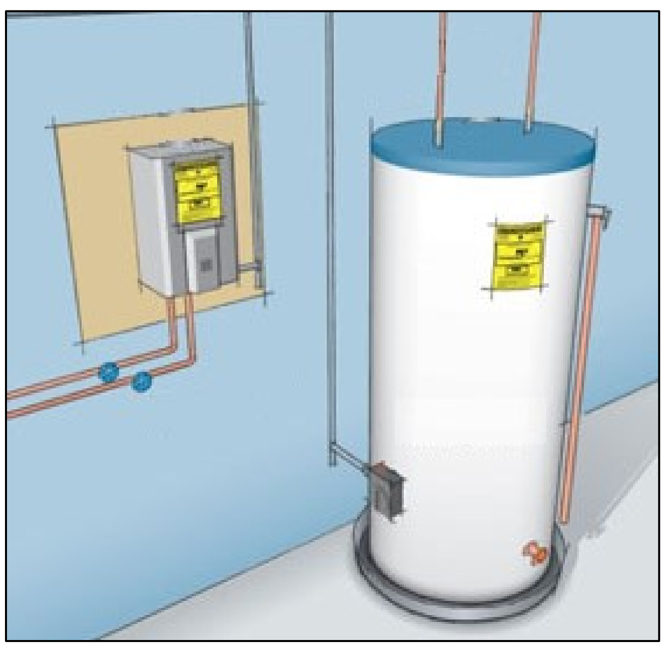

Figure 4.9 Tankless water heater (left) and tank water heater (right) (adapted from Water Heater Hub (2016))

These water heaters heat water from the inlet temperature (~9-18°C) (George et al. 2015) to the desired delivery temperature (~52°) nearly instantly which requires a larger power supply than a traditional water heater with a tank. Whole-home electric tankless water heaters that deliver up to 27 kW of power have recently been made available at local building supply stores for reasonable prices (Home Depot of Canada Inc. 2016). Such loads can have a significant impact on a whole-house load profile. This sub-section uses the measured DHW consumption profiles to analyze the potential impact of implementing tankless water heaters on the peak demand of houses.

4.3.1.1 Methodology

For this analysis, energy calculations are conducted manually on the DHW profiles rather than by using a building simulation software. Water heating power requirements are calculated using Equation (3).

$$Water\ Heater\ Power = \dot{V}\rho c_p \Delta T \tag{3}$$

To satisfy Equation (3), the density (ρ) and the specific heat capacity (c_p) of water are assumed to remain constant at values of 1 kg/m^3 and 4.182 joule/gram °C. The change in temperature (ΔT) across the water heater is calculated using the inlet temperatures provided by the building simulations and a desired DHW temperature of 51.8 °C based on the findings of George et al. (2015). Since the inlet temperatures were consistent across households (within 0.9 °C for any given time-step), the same inlet temperature profile is used for all households. Lastly, the DHW profiles provide the volumetric flow rate ($\dot{V}$).

First, the DHW profiles were adjusted to ensure they best represented 'flow rate' in L/min. For example, if a DHW draw lasts for less than the 1-minute time-step length, the measured DHW consumption may not actually equate to rate of flow. To correct this, the same logic of Section 2.3.3 was applied to adjust the DHW profiles to be more realistic for water heater power calculations:

- S*ingle values* are unadjusted.
- *Double values* are adjusted so that the flow rate for both values is equivalent to the larger of the two.
- *Non-edge values* are unadjusted.
- *Edge values* are adjusted to that they are equivalent to the preceding or following measurement, but only if that value is larger than the edge value.

See Section 2.3.3 for a thorough description of each category of measurement.

4.3.1.2 Time-step Analysis

The time-step water heater power draw and DHW consumption between 15h to 18h are shown in Figure 4.10 for both a conventional water and a tankless water heater.

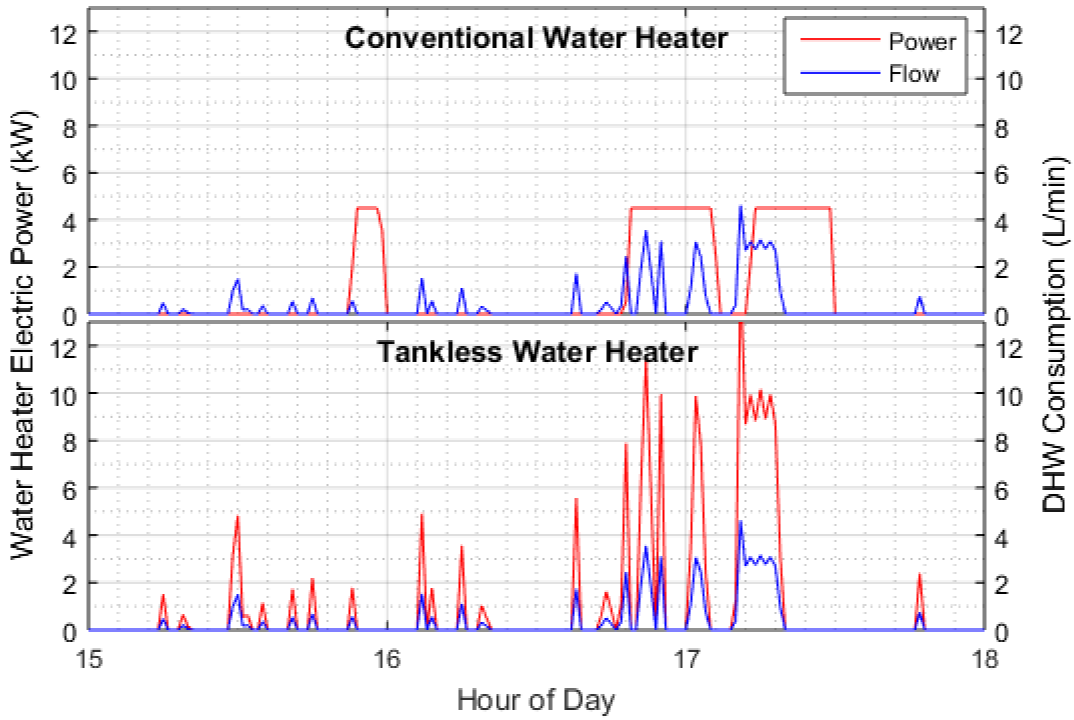

Figure 4.10 Time-step water consumption and water heater electrical power of conventional and tankless water heaters

From Figure 4.10, an instantaneous water heater will draw much more power than a conventional water heater and it occurs at the time of use whereas a conventional water heater can see a delay in power draw due to hysteresis control around the DHW temperature setpoint.

The influence of water heater power on the whole-house load profile is now demonstrated in Figure 4.11 for the two water heater types during a winter and summer day.

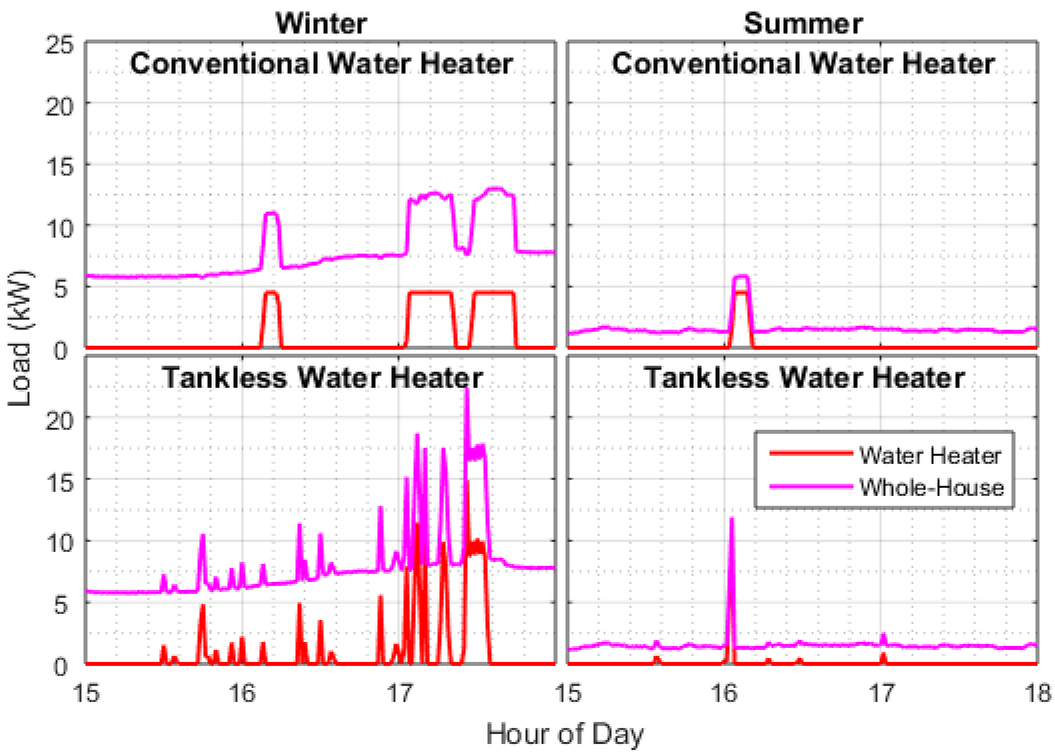

Figure 4.11 Example of water heater and whole-house loads during the summer and winter for conventional and tankless water heaters

From Figure 4.11, both types of water heaters can cause whole-house loads to fluctuate, however, from the upper left plot, the water heater only increases the magnitude of the house load by a factor of two and is engaged three times during the time-period. In the lower left plot, the tankless water heater is engaged many times during the time-period and increases the house load by up to 400%. In the right hand plots, the whole-house load during the summer season is much lower, magnifying the overall impact that using a tankless water heater has on the whole-house load.

4.3.1.3 Limitations of Tankless Water Heaters

At times, a DHW draw may be too large for an tankless water heater to satisfy the load. This is explored for each of the 82 DHW consumption profiles by calculating the percentage of DHW draws that would require more than 27 kW to reach the desired outlet temperature. These are shown in Figure 4.12.

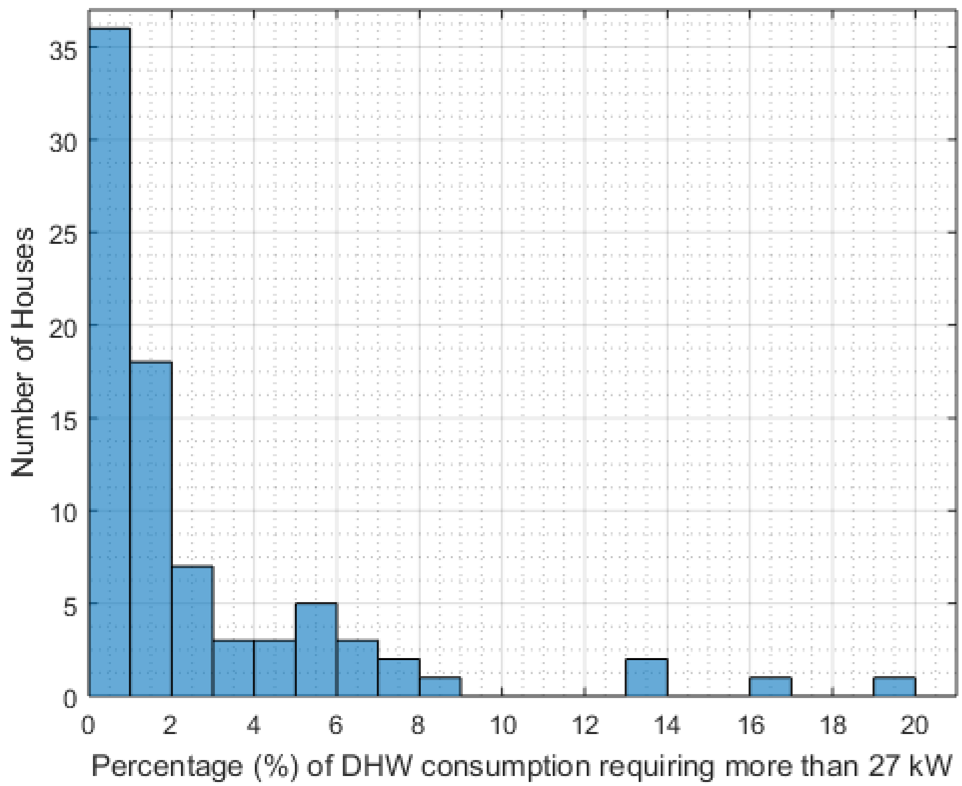

Figure 4.12 Distribution of percentages of DHW draws requiring more than 27 kW power for all households (n = 82)

From Figure 4.12, it is clear that the majority of houses will rarely lack a water supply at the desired temperature. However, for 5% of households, a 27 kW tankless water heater would be insufficient over 13% of the time.

4.3.1.4 Potential Impact of Tankless Water Heaters on Whole-House Loads

The high magnitude power draws of tankless water heaters could also cause issues at the electrical panel in a household. For example, a 200 A breaker on a 240 V circuit could support a maximum power draw of 48 kW. This section evaluates the chance of exceeding this limit if high water heating loads happen concurrently with high space heating and ALP loads. To accomplish this, the tankless water heater power profiles are matched with the simulated ER house HVAC and ALP load profiles and the annual peak load is evaluated. A total of 1640 profile combinations are tested (82 DHW profiles and 20 HVAC/ALP profiles). The distribution of maximum and 98th percentile loads are shown in Figure 4.13.

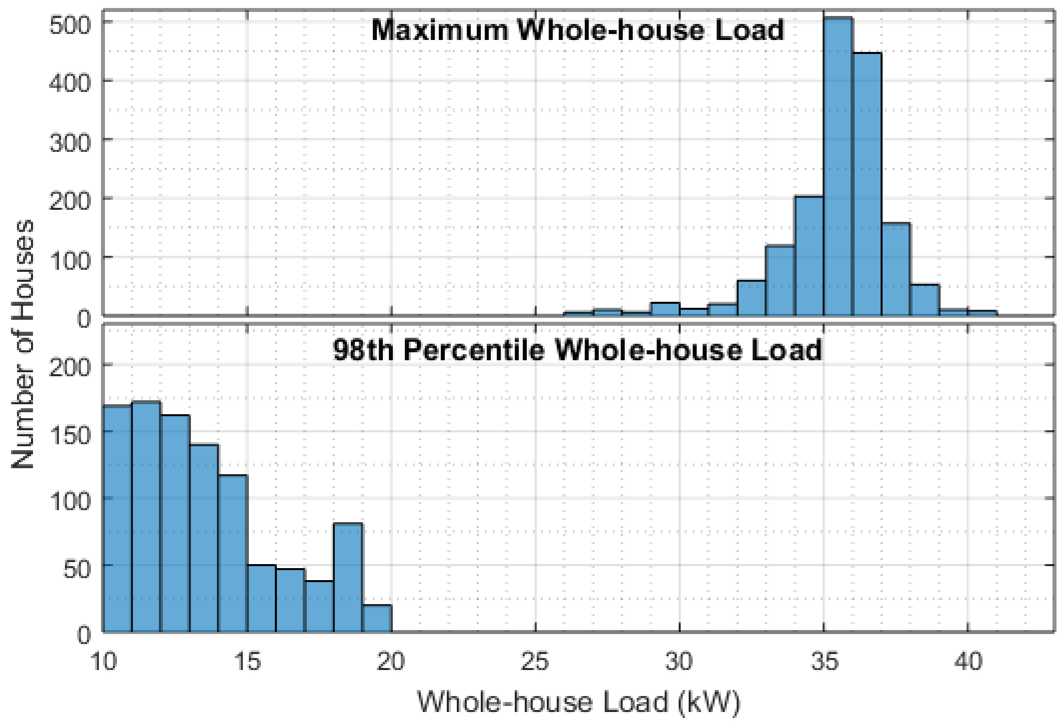

Figure 4.13 Distribution of maximum and 98th percentile whole-house loads for various tankless water heater, HVAC and ALP load combinations (n = 1640)

From Figure 4.13, none of the water heater and HVAC/ALP profile combinations produce a whole-house maximum load beyond 41 kW and 98% percent of loads are within 20 kW, suggesting that for these households, a limit of 48 kW would not be exceeded.

4.3.1.5 Community Aggregation of Tankless Water Heater Loads

Electricity providers may be concerned with the volatility of tankless water heater loads and their aggregate impact on the electricity grid. This sub-section explores the aggregation effects of community scale uptake of tankless water heaters. First, a 1-minute time-step, three hour tankless water heating load profile of a range of community sizes (1, 20, 40 and 82 houses), is shown in Figure 4.14.

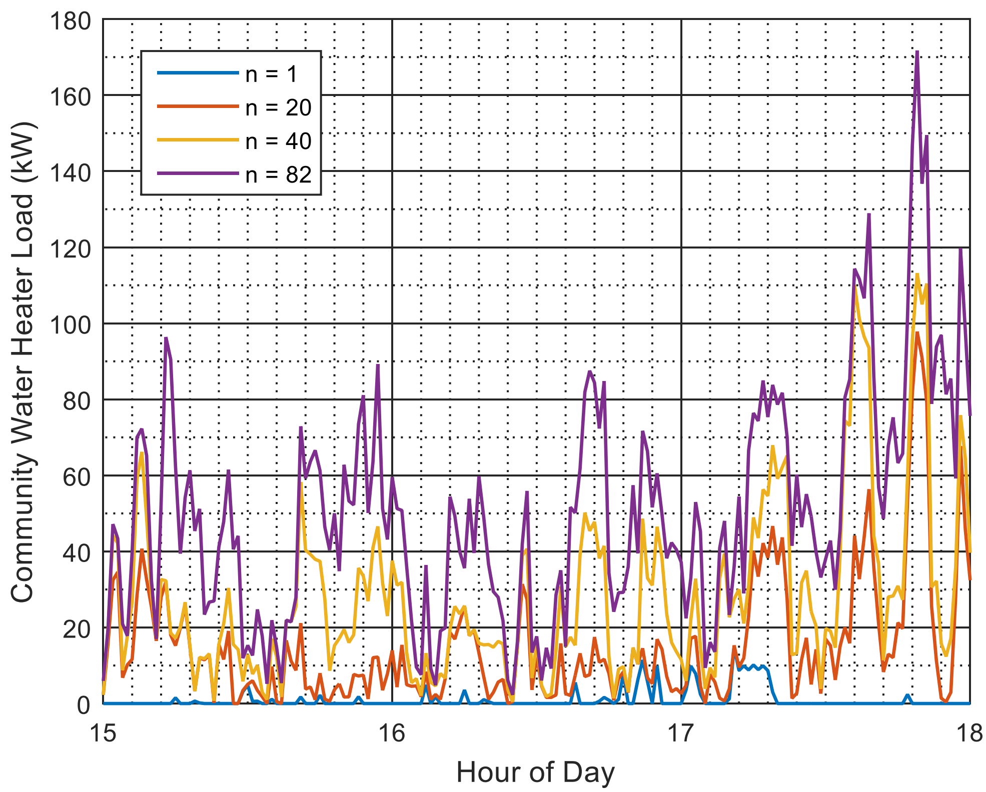

Figure 4.14 Time-step DHW heating load of various community sizes with tankless water heaters

From Figure 4.14, the aggregate tankless water heating loads appear to be volatile even as the number of houses increases from 1 to up to 82 houses. Despite the temporal variation in DHW consumption across households shown in Chapter 2, the community load does not become much smoother as the number of homes increases. This is due to the 'instantaneous' nature of tankless water heaters and the sporadic nature of DHW consumption. The heating element is only engaged when DHW is being consumed and since most of the time the DHW load of a household is zero, the water heating load of a house can shift from zero to up to 100% (up to ~27 kW) very quickly. Since tankless water heaters can draw a larger load, it could require relatively few households to significantly increase the community load in one time-step. Next, the load changes associated with the full community water heating load (n = 82) are shown in Figure 4.15. The average load changes that appear during each hour of the day are represented by the red asterisks while the 2nd and 98th percentile loads are contained within the red error bars and the minimum and maximum load changes are contained within the blue error bars.

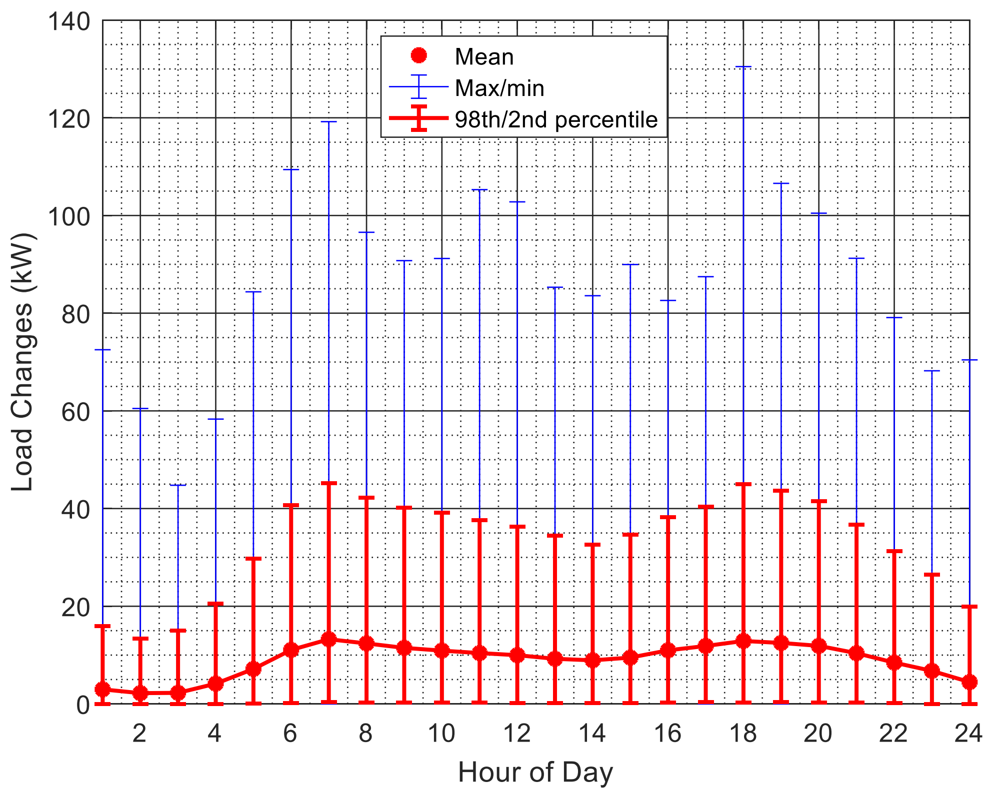

Figure 4.15 Average, 2nd, 98th, minimum and maximum hourly load changes of community tankless DHW heater loads (n = 82)

From Figure 4.15, the majority of load changes (98%) of the community are within 45 kW but much higher load changes of up to 130 kW do occur. However, this value is still relatively small compared to the potential maximum load of the community (i.e. if all homes fully engaged their tankless water heaters concurrently, the maximum load would be 27 kW X 82 houses = 2214 kW). To explore how the maximum load changes are influenced by community size, the maximum load change is shown in Figure 4.16 for graduated sizes of communities with both tankless and tank water heaters. Only 20 whole-house simulations were conducted due to the limited number of 1-minute ALP profiles, and so the conventional tank water heater community size is capped at 20 houses.

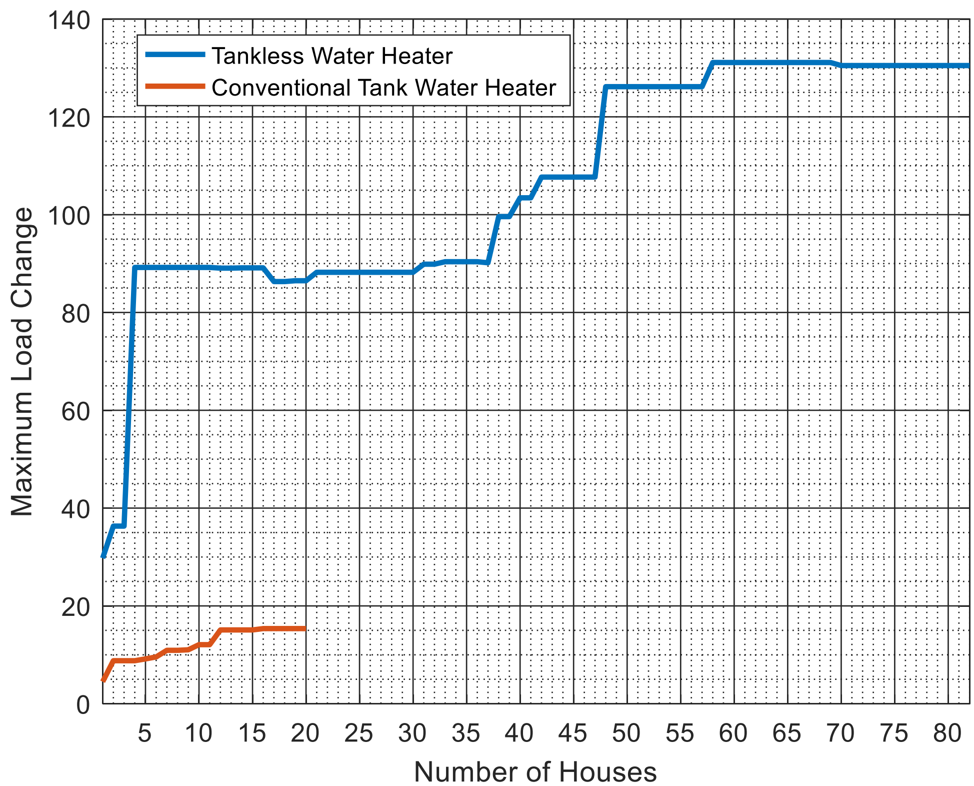

Figure 4.16 Graduated tankless water heater load changes with increasing size of community

From Figure 4.16, the peak community water heating load changes increases by a specific amount each time a new profile has DHW consumption at the same moment as the current maximum load change. As more tank are added to the community, the maximum load change could continuously rise, rather than peaking at a specific value. While this is the same for tankless water heaters and conventional tank water heaters, the peak tankless community load change increases at a much faster rate. For this reason, an electrical utility might be concerned about the mass uptake of whole-house tankless water heaters.

4.4 Economic Application: Time-of-Day Pricing

Time-of-day (TOD) electricity pricing is a way for electric utilities to influence the uptake of powershifting technologies. An example of such a technology is electric thermal storage (ETS) space heating systems which heat up a thermal mass during periods of low electricity rates and release the heat to the house during periods of higher electricity rates so that less electricity is required from the utility during the 'higher' rate period. The electricity provider in Nova Scotia, NSPI, offers two domestic electricity pricing schemes: the domestic service tariff which is available to all customers and the domestic service TOD tariff which is only available to homeowners who have an ETS heating system installed. The non-TOD rate is 0.148 $/kWh and the TOD tariff schedule is shown in Figure 4.17.

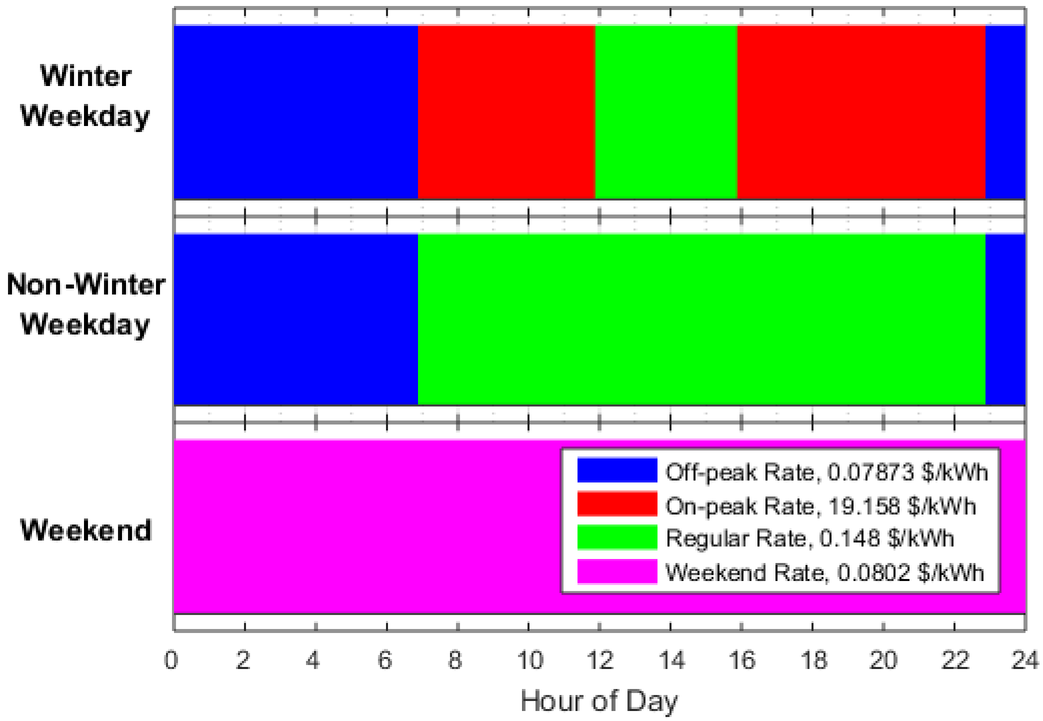

Figure 4.17 NSPI domestic service time-of-day tariff schedule (NSPI 2016)

If the TOD tariff was made accessible to all customers, then homeowners may opt for this tariff for reasons other than their heating system type. One example that might not influence space heating or cooling or existing ALP loads would be the purchase of an electric vehicle (EV) that could be charged on the off-peak rate times. To understand if this option is financially reasonable for a homeowner, the effect of TOD pricing on all other electricity consumption should be understood. The annual electricity expenditures under both NSPI tariffs have been calculated for the each of the 82 houses with three heating system types and the distributions of these rates are shown in Figure 4.18 and the statistics of the difference between the two tariff distributions are shown in Table 4.4.

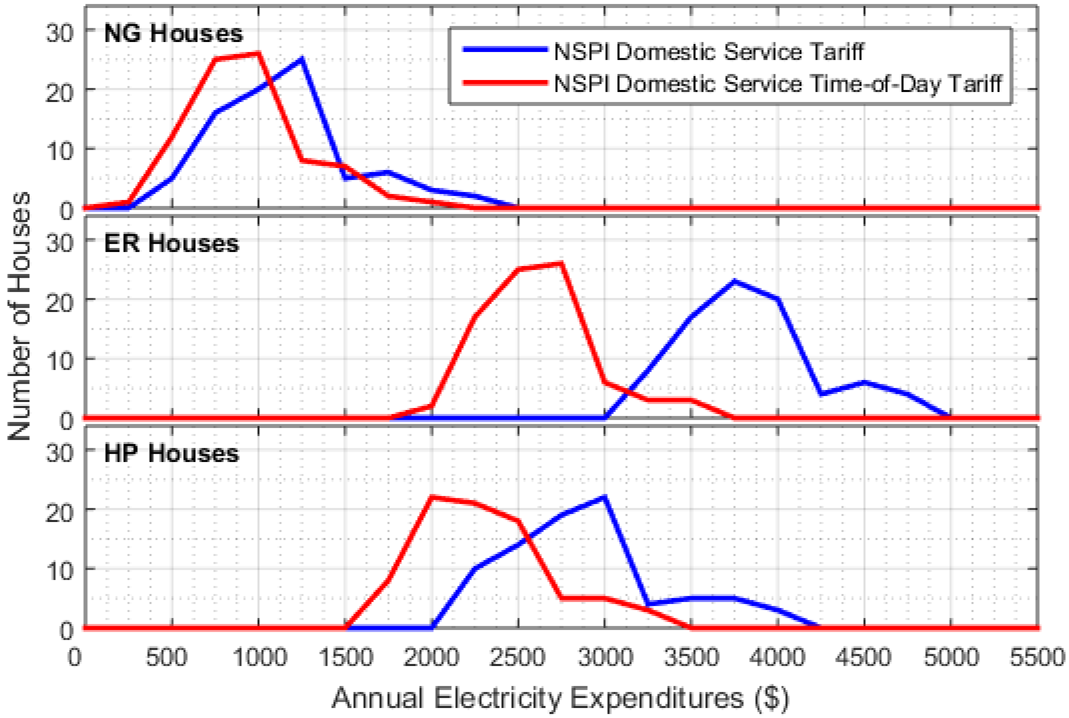

Figure 4.18 Distribution of annual household electricity costs across for various heating system types for standard and time-of-day pricing schemes

Table 4.4 Statistics of decrease in annual electricity expenditures from standard to TOD electricity tariffs for three heating system types

	Decrease in annual electricity expenditures ($ CAD)		
Statistic	NG houses (n = 82)	ER houses (n = 82)	HP houses (n = 82)
Mean	$ 200.95	$ 1,212.11	$ 578.47
Median	$ 189.19	$ 1,195.00	$ 572.07
Maximum	$ 406.46	$ 1,460.99	$ 793.65
Minimum	$ 84.59	$ 1,074.55	$ 456.43

From Figure 4.18 and Table 4.4, all three categories of homes show a general decrease in annual electricity expenditures under the TOD tariff compared to the standard rate. For NG houses, the decrease is marginal, with an average decrease of $200.95 annually. The average decrease for electrically heated homes is much more with a $1,212.11 decrease for ER homes and a $578.47 decrease for HP houses. It should be noted that all houses in each heating system category were identical in construction and therefore are subject to very similar heating loads. The NG houses show much more variation on account of variations in occupant load time-of-use characteristics across homes.

Based on these findings, the utility would generally lose income if homeowners had access to the TOD tariff, even if homeowners did not change their behavior.

4.4.1 Evaluation of Tank and Tankless Water Heaters Under the non-TOD and TOD tariffs

This subsection elaborates on the analysis of Section 4.3 by evaluating tankless and tank water heaters under non-TOD and TOD electricity rates. Tankless water heaters consume electricity at the time-of-use, whereas tank water heaters will delay electricity consumption, so presumably, a TOD rate structure could impact DHW heating expenditures. This analysis is conducted for ER houses only, since DHW consumption profiles are the same between house types and so the results would be very similar HP houses which also rely on electricity for water heating. Table 4.5 shows the annual DHW heating electricity consumption and the associated expenditures under the non-TOD and TOD tariffs.

Table 4.5 Annual electricity expenditures under standard and TOD electricity tariffs for tank and tankless water heaters

Tariff	Annual Electricity Consumption (kWh)	Annual electricity expenditures for DHW heating ($ CAD)		
		Domestic Service Tariff	Domestic Service TOD Tariff	% difference
Tankless Water Heater (n = 20)	2548	$ 377.12	$ 343.33	-9.0%
Tank Water Heater (n = 20)	2750	$ 407.03	$ 376.65	-7.5%

From Table 4.5, 7.3% less electricity is consumed by a tankless water heater than a tank water heat, presumably due to stand-by heat losses through the tank envelope. This equates to 7.3% lower electricity expenditures under the non-TOD. Under the TOD tariff tank water heaters experienced greater annual cost savings on average (9.0%), compared to tankless water heaters (7.5%). However, this effect is not consistent across households; some households will actually spend more money for DHW heating under a TOD tariff suggesting that some households don't necessarily consume DHW during typical peak-rate hours. This is explored further in Figure 4.19, which shows the change in annual expenditures from switching from the non-TOD to TOD tariff for both water heater types.

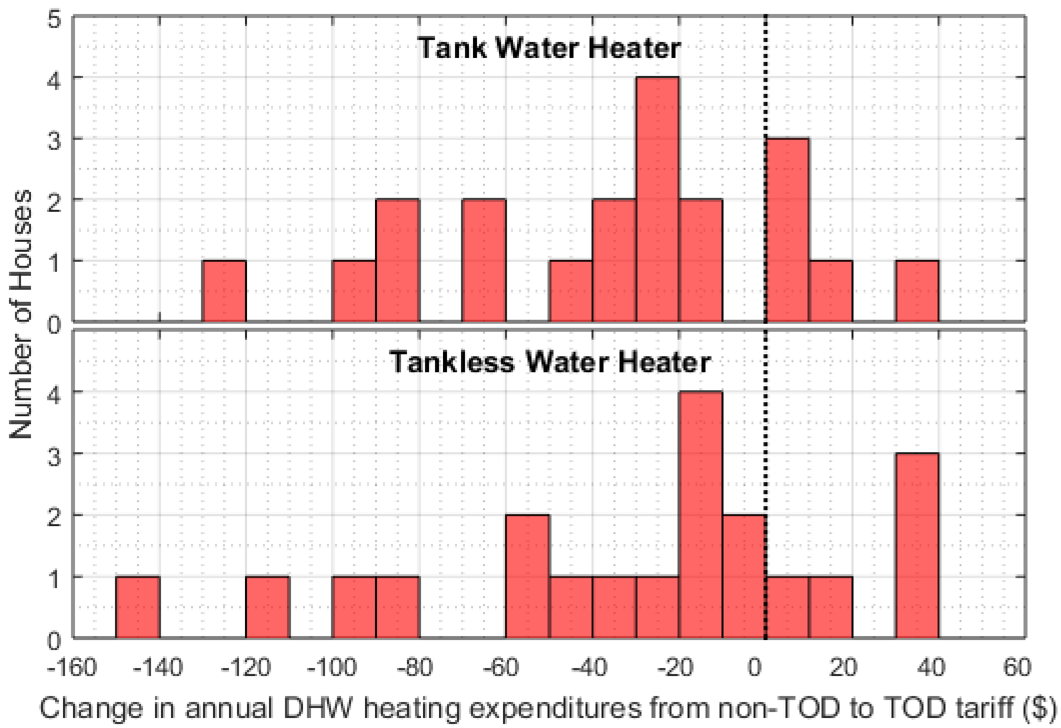

Figure 4.19 Distribution of changes in annual electricity expenditures under non-TOD and TOD tariffs for tank and tankless water heaters (n = 20)

From Figure 4.19, while most users show an decrease in expenditures due to the TOD tariff, not all do. Users may experience a decrease of as low as $143.00 or an increase as high as $40. Surprisingly, changes are quite well distributed for both water heater types which can likely be accounted for by variation in consumption patterns of specific households as well as between households.

4.5 Conclusions

The comparison of building simulation results using existing, synthetic occupant load profiles and the new measured occupant load profiles highlights the benefits and limitations of both. Two primary benefits of the measured dataset are apparent: (1) their high temporal resolution, and (2) the variety of profiles.

The default profiles are particularly limited in both time-step resolution and variability. Furthermore, they show 70% more DHW consumption and 51% more ALP electricity consumption than the measured profiles on average.

The major limitation of the synthetic profiles is that there are only 3 annual DHW profiles and 9 ALP profiles so they will not permit demand (power) modeling of communities or the evaluation of profiles across a variety consumer types.

The 1-minute time-step measured data provides opportunity for demand modeling of technologies. This has been demonstrated with the modeling of tankless water heaters where it was shown that for a small percentage of households, a 27 kW tankless water heater may not be capable of providing water at a desired temperature up to 20% of the time for a small number of households. An analysis of the impact of tankless water heaters on whole-house profiles was also conducted and it was shown that there is little likelihood that a tankless water heater could cause a whole-house load that is beyond the limits of a typical electrical panel.

Lastly, an economic application was demonstrated by evaluating the whole-house building simulation results against a standard electricity tariff in Nova Scotia and a TOD tariff. It was shown that without any change in behavior, average homeowners would spend less on electricity.

The new occupant load profiles enable such analyses to cover a wide range of user types and an entire year of temporal variations. It is hoped that these profiles will be applied by in the future by researchers to conduct similar evaluations. For example, comparisons could be made between competing technologies such as drain water heat recovery, solar DHW heating systems and solar PV under various electricity import and export rate structures. Futhermore, this short demonstration could be elaborated further with the following suggestions:

- different heating system types that are designed to temporally shift energy consumption for space heating and cooling could be modeled (e.g. ETS systems),
- heating and cooling control strategies could be varied to demonstrate how a homeowners could influence their electricity expenditures using programmable thermostats
- occupant load data from homes with a TOU rate could be measured and developed.

Chapter 5 Application of Occupant Load Profiles to Community Scale Simulation

The primary benefit of the new measured occupant load profiles is a significant advancement in the ability to perform time-step demand modeling of communities because they capture the variations in occupant behavior within a community. This allows for the use of unique profiles for each house in a community, avoiding unrealistic peak loads that occur by repeating a limited number of occupant load profiles for multiple houses. In this Chapter, the new measured occupant load profiles are incorporated into the residential Archetype building models described in Chapter 4. and other minor adjustments are made to the models to simulate a more realistic community. The building models then underwent a batch simulation to evaluate the whole-house electricity load of a hypothetical tract home community of 82 identical homes.

5.1 Background and Literature Review

Previous research has focused on energy and greenhouse gas emissions modeling on a community scale. For example, Han et al. (2015) simulated solar PV in combination with proton exchange membrane fuel cells (PEMFC) for a neighborhood 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 the 12 load profiles developed by Saldanha and Beausoleil-Morrison (2012) were summed to represent the ALP load of the community. The results demonstrated an 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 modeling 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, the limited set of nine ALP profiles generated by Armstrong et al. (2009) and the three DHW consumption profiles generated by Jordan and Vajen (2001a) 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.

Since its development, the CHREM has been used for several community scale studies investigating solar DHW heating system retrofits, window shading retrofits, internal combustion engine based cogeneration systems, solar combi-system retrofits, and air-to-water heat pump retrofits (Nikoofard et al. 2014a, Nikoofard et al. 2014b, Asaee et al. 2015, Asaee et al. 2016, Asaee et al. 2017). These studies were focused on aggregate energy consumption of homes, rather than time-step demand. However, Wills et al. (2016) employed the CHREM to conduct a time-step evaluation of source net-zero performance for residential community scale solar PV retrofits using a new set of synthetic ALP profiles generated for the study (see Section 3.2 for an overview of these profiles).

Several Canadian based studies have been conducted in recent years examining optimal neighbourhood design for solar communities, including strictly residential communities (Hachem et al. 2012 and Hachem et al. 2013) and mixed-use communities (Hachem 2015, Hachem 2016). Factors such as plan shape of housing units (e.g. L-shape or rectangular), roof design, site layouts and community density where considered. For each residential building, the same profiles for DHW heating, lighting, and major and minor appliance electricity use were applied. These studies also focused on aggregate energy consumption of homes, or energy demand at low time-step resolution (hourly).

5.2 Community Layout

The Archetype Models of Portland, Maine that were simulated in Chapter 4 were again selected for the community simulations. Since a new, tract home community could be reasonably constructed with common heating system types throughout, three communities are modeled to represent communities of electrically heated homes with electric resistance furnace (ER) heating systems, heat pump (HP) heating systems, and non-electrically heated homes with natural gas (NG) furnaces. See Table 4.1 in Section 4.1.2 for a detailed description of individual house models.

The communities consist of 82 houses with various orientations to represent a realistic configuration. A sketch of the community is shown in Figure 5.1 where each black square represents a house and the smaller, white grid on each house represents a solar PV array.

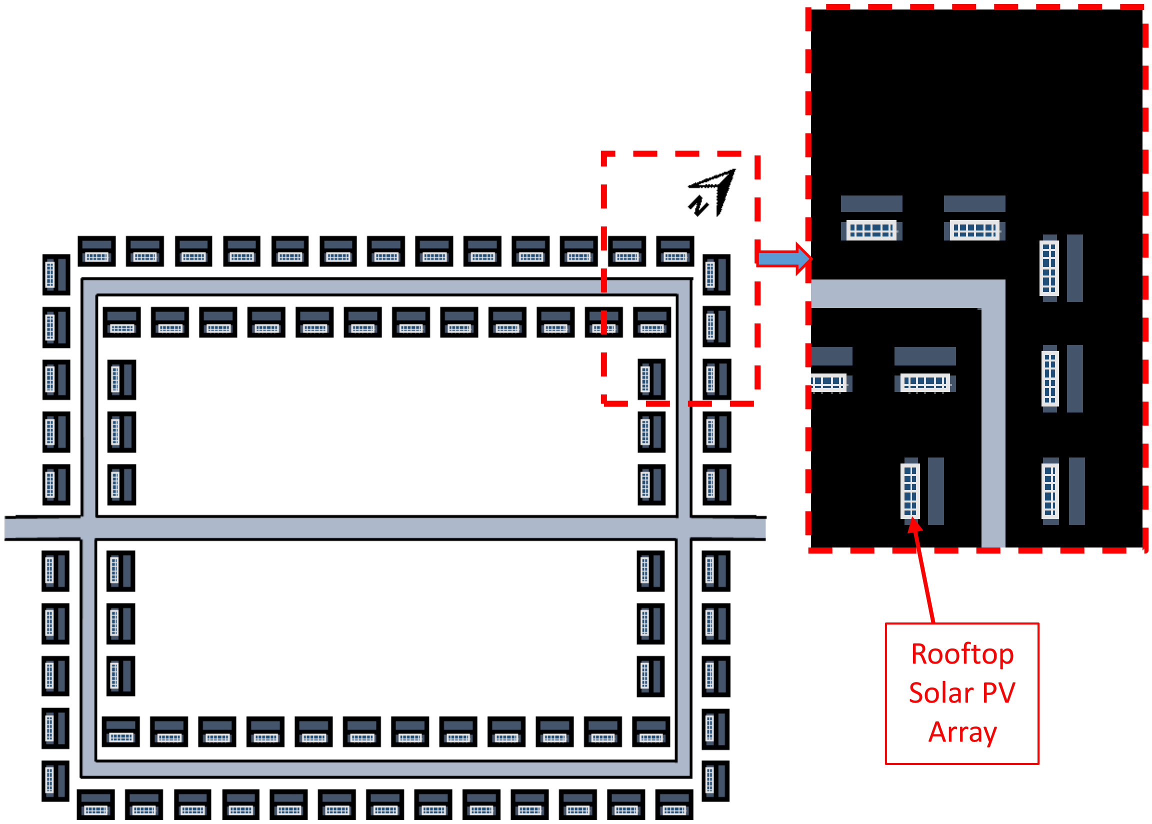

Figure 5.1 Sketch of community layout

In Figure 5.1, single detached houses are located on evenly divided parcels of land. A major road intersects the community, creating two mirrored U-shaped residential streets. The community is oriented so that all homes have a sloped gable roof facing within 45° of South. Shading between houses is not being taken into account in this study.

As in the previous Chapter (see Section 4.1.4.3), the DHW and ALP datasets were sorted based on lowest to highest average consumption and paired on this basis and these 82 profile pairs were randomly distributed to house models throughout the community.

Lastly, a rooftop 5 kW PV system was applied to each house (shown by the grey and black grid on the roof of each house in Figure 5.1). The PV systems are located on the most south facing roof of each house with an 18.5° tilt to match the slope of the roof.

Each house in the community was then simulated for an entire year at 15-minute time-steps and the community loads were calculated by summing results from community. Additionally, the subset of 20 houses with a 1-minute time-step ALP profile from the Ottawa dataset were simulated at a 1-minute time-step and community loads for this subset were calculated in the same fashion.

5.3 Simulation Results Analysis

In this section, three output variables generated from the EnergyPlus building simulations are analyzed:

- Whole-house electricity load - this is the total electric demand power the whole building ALP and HVAC electric demands averaged over the time-step
- PV power - this is the total photovoltaic electricity produced on-site in power units
- Water heater electric power – this is the electricity demand for the DHW heater element averaged over the time-step

From PV power and the whole-house electricity load, the 'net house load' can be calculated, where a negative value would signify an electricity export to the electrical grid and a positive value would signify import from the electrical grid.

5.3.1 Aggregate Energy Consumption and Generation

First, aggregate ALP and whole-house energy consumption and PV power generation for the three communities of different heating system types (NG, ER and HP) are presented in Figure 5.2.

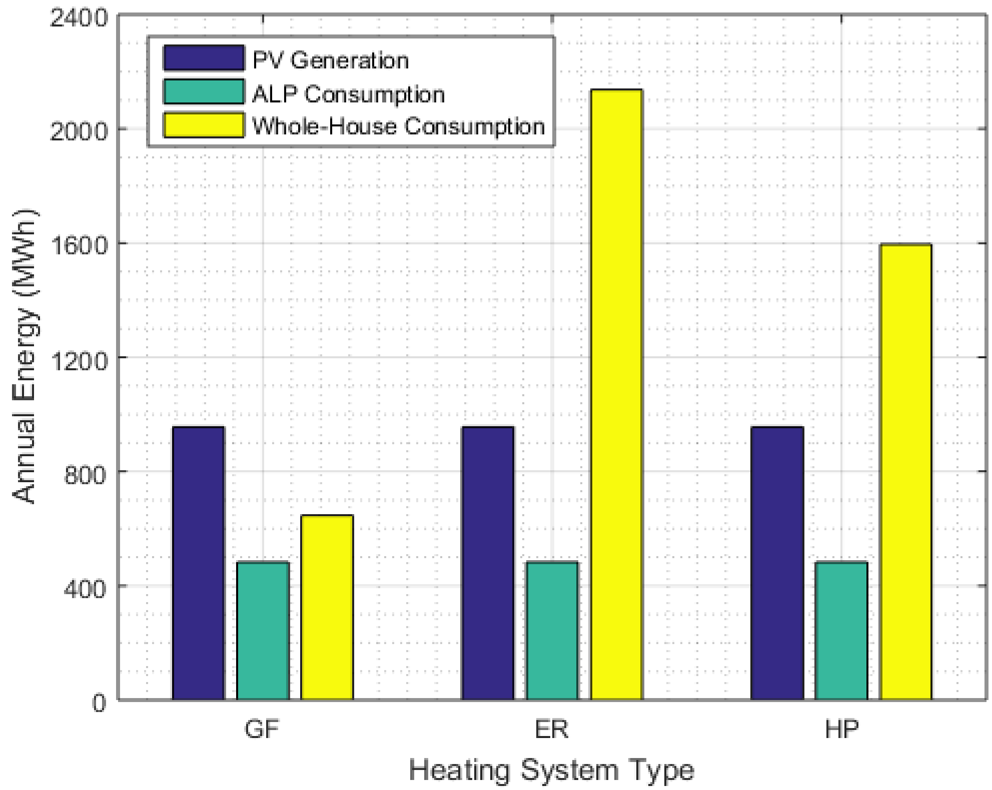

Figure 5.2 Annual energy consumption and generation of modeled communities

From Figure 5.2, PV energy generation and ALP energy consumption are identical for each community, but whole-house energy consumption changes on account of electric space heating and space cooling (note that all communities are equipped with electric space cooling, regardless of heating system type). For NG houses, the whole-house consumption is approximately 65% of PV generation, but for the electrically heated communities, PV generation is less than whole-house consumption.

Annual estimates such as these can be used to evaluate whether a community is 'net-zero' or to satisfy the requirements of a net-metering program where distributed generation must be less than community energy consumption.

5.3.2 Demand Analysis

Figure 5.3 shows the average hourly consumption and PV generation of the community during winter and summer for the three heating system types.

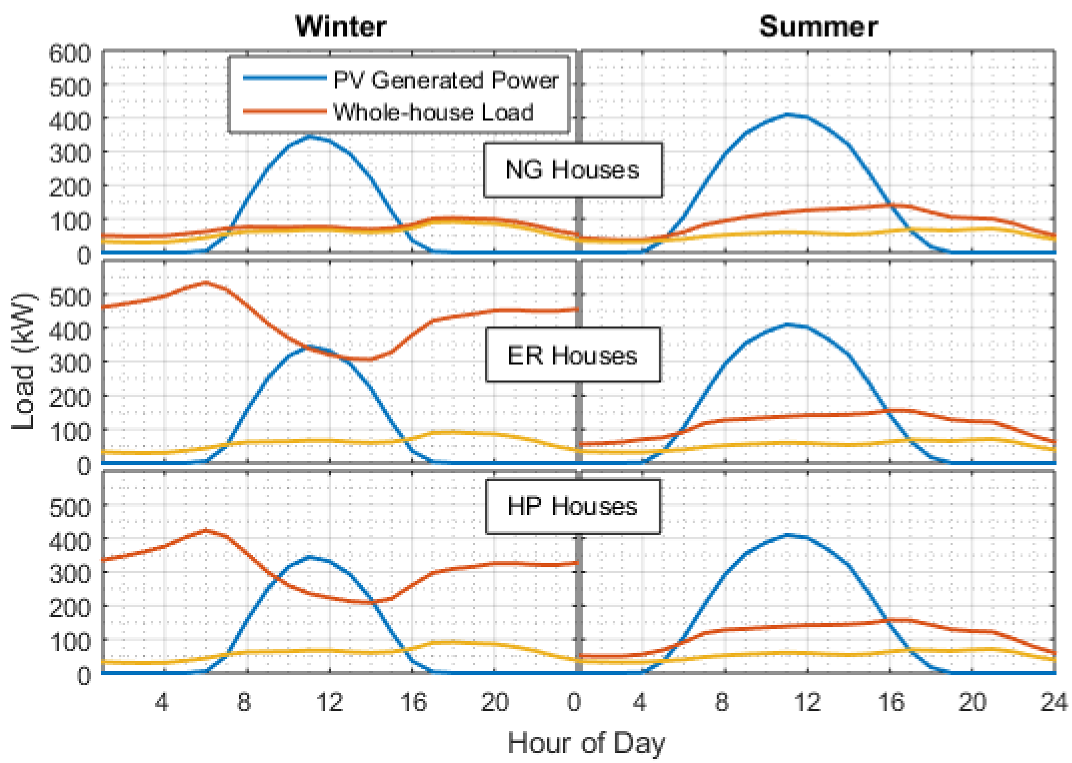

Figure 5.3 Average hourly community loads and PV power generation (n = 82) during winter and summer seasons for three heating system types at a 15-minute time-step

From Figure 5.3, the average relationship between PV generation and community loads is shown for the winter and summer seasons. Even though ER and HP houses consume more energy than is generated on an annual basis, much more electricity is generated during daytime hours (6h-16h) than is consumed by the community during summer months. Even during the winter season for HP houses there is a period where generation exceeds consumption (between 9h and 14h).

The resolution of this analysis is increased further in Figure 5.4 where the 1-minute time-step loads and generation of a single ER house and a 20-house subset of the community are shown.

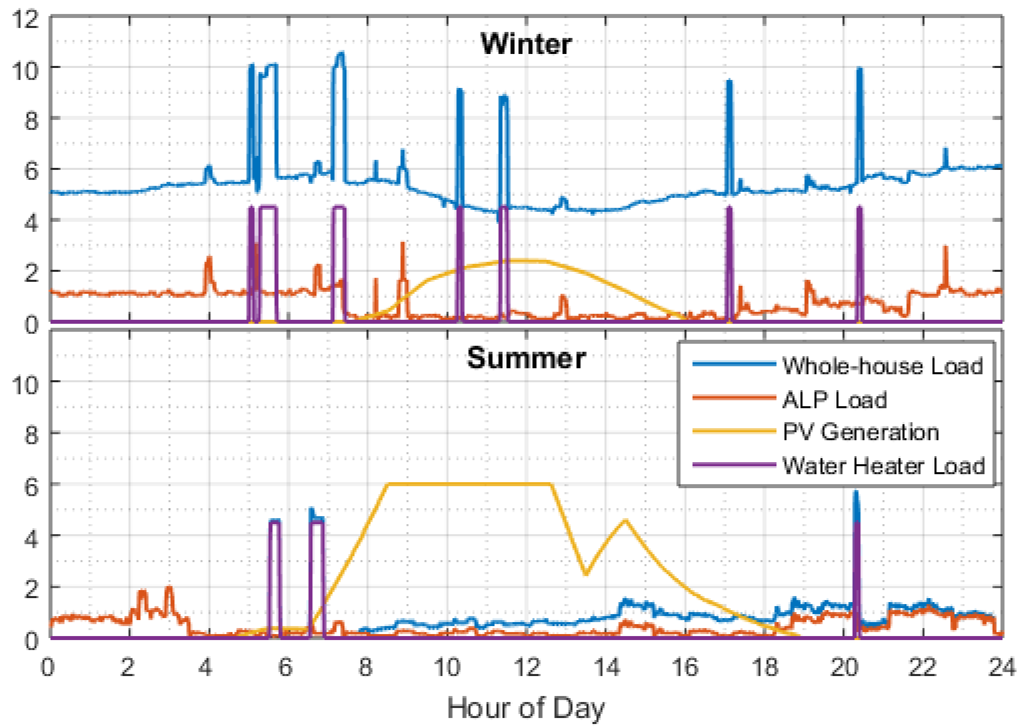

Figure 5.4 Example of ALP load, whole-house load and PV generation at a 1-minute time-step for a single house of ER type

From Figure 5.4, the direction of flow of electricity to or from a house can change frequently throughout a day, especially during the summer months due to water heater and large ALP loads or abrupt changes in solar radiation due to cloud cover. It is also notable that for this house on this day, activity in the household begins just as PV generation ceases, which is apparent by the rise in ALP load at 18h and the large ALP loads occurring shortly thereafter. The significant effect of the DHW load on the whole-house loads also flags the potential of controlling DHW heaters during periods of high demand on the electrical grid.

The load for 20 houses (including the house shown in Figure 5.4) is now shown in Figure 5.5 for the same day.

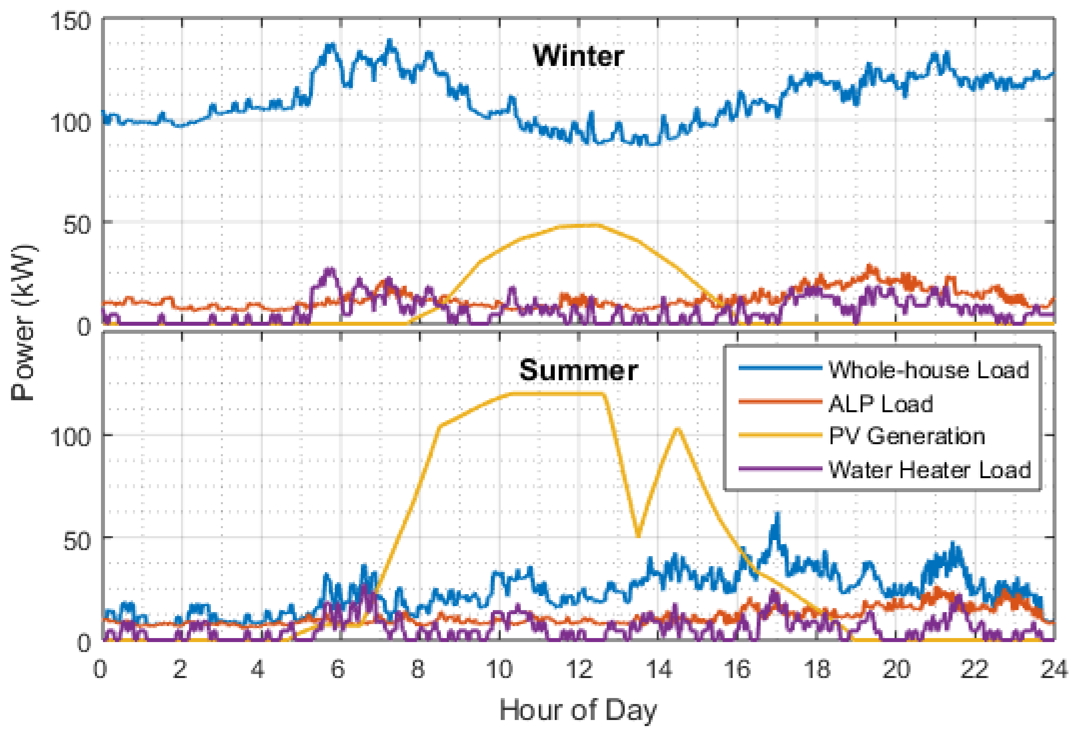

Figure 5.5 Example of ALP load, whole-house load and PV generation at a 1-minute time-step for a community of 20 houses of ER type

From Figure 5.5 the ALP load profile and therefore the whole-house load profiles are much smoother than for a single house. This demonstrates the variability of occupant consumption patterns.

5.3.3 Electrical Grid Imports and Exports

While the figures in Section 5.3.2 show the breakdown of various load types in the community, utilities are only concerned with the net-load from the community so that they can procure sufficient capacity to balance the load. For one shoulder season day (March 2nd), Figure 5.6 shows the net community load for 82 houses (thick black line) scaled down by a factor of 82 and the net-load for 5 houses in the community (shown by thin, colored lines). Only 5 individual house profiles are used so that fluctuations can be clearly seen. The PV power generation of the community is also shown (thick red line) and scaled down by 82 for comparison.

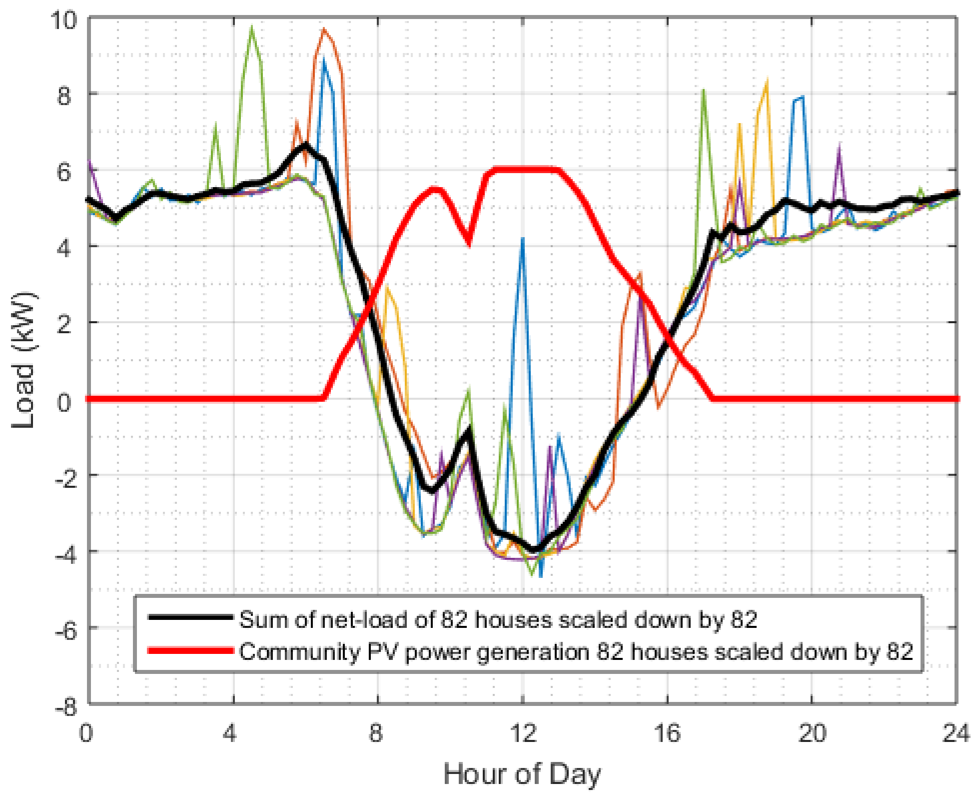

Figure 5.6 Time-step profile of net-load of 5 ER houses (thin colored lines), scaled community net-load (thick black line, n = 82) and scaled community PV power generation (thick red line, n = 82).

From Figure 5.6, electricity is both exported to and imported from the grid on this day. The community load is sharply affected by the reduction in PV power generation at approximately 10h because climate factors such as cloud cover are coincident over the entire community. However, the net community load is generally unaffected by the sharp fluctuations seen in the individual household loads, which are not coincident across the dataset. Since each household is of the same construction the individual household load fluctuations are primarily due to variations the occupant load profiles. This variation across households is explored further in Figure 5.7, which shows the seasonal average net house loads for each household in the community for the three heating system types.

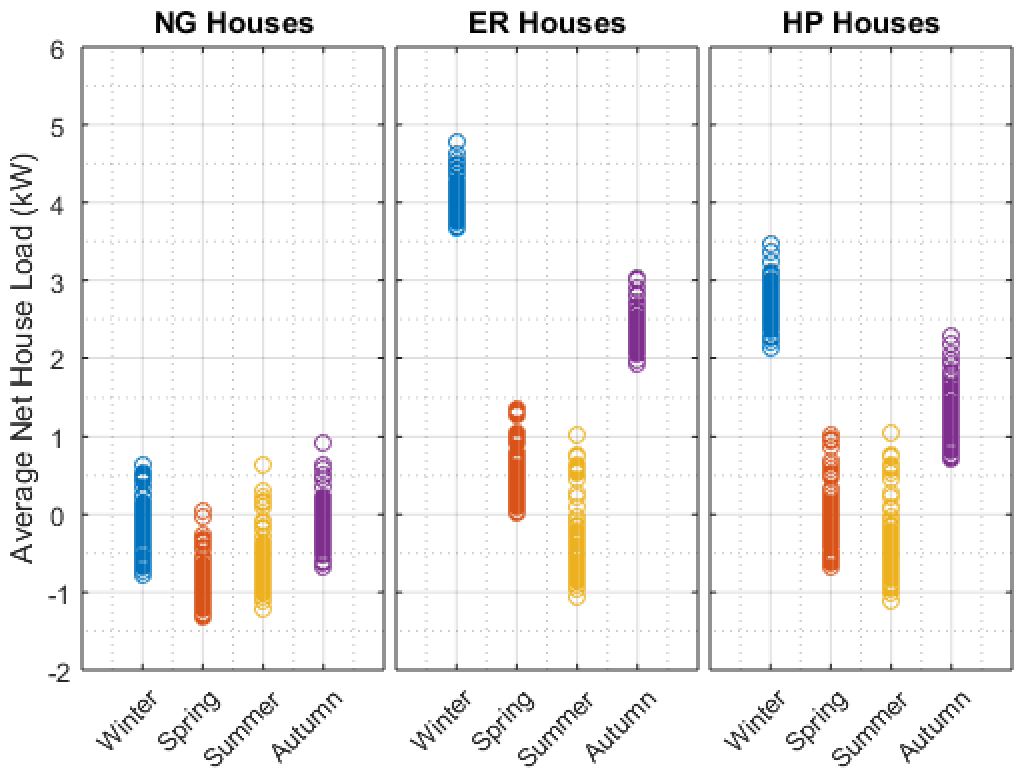

Figure 5.7 Distribution of net seasonal electricity exports across all homes for three heating system types

Figure 5.7 shows that the distributions of average net-loads from each house in the communities' range by roughly 1 kW to 2 kW for each season and in many cases, the range can cross the threshold between net electricity imports and exports to the electrical grid from the community. This analysis could be applied for a real community to determine the PV capacity necessary for a community to be 'net-zero'.

5.3.4 Peak-to-Mean Ratios

5.3.4.1 Individual Houses

One way to evaluate the fluctuation of a load is to calculate it's 'peak-to-mean ratio'. In Section 3.5.4, the peak-to-mean ratios of ALP loads were examined for individual households and community scenarios and it was determined that time-step and size of community influenced the peak-to-mean ratio of an ALP load profile. However, what is more relevant to the designers and energy providers of communities are the whole-house loads. This section examines the peak-to-mean ratios of the simulated whole-house loads for the communities with three heating system types. Note that PV power production is not taken into account.

In Figure 5.8 the relationship between the annual peak and mean whole-house loads are explored. As well, ALP values are included for comparison.

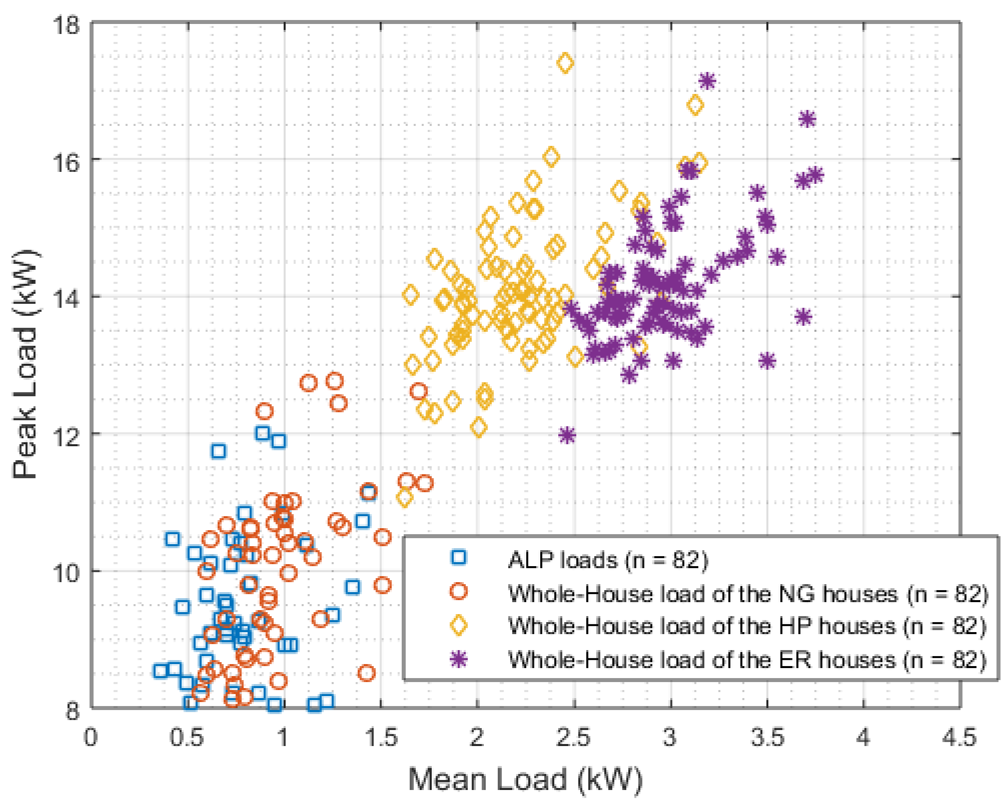

Figure 5.8 Annual peak whole-house electricity loads vs. annual mean whole-house electricity loads for individual houses

For all load types shown in Figure 5.8, peak loads are independent of mean loads. ER houses have the highest mean loads, but the peak loads are comparable to the HP houses. This suggests that the heat pumps can draw a similar magnitude of power as electric resistance heaters, but are more efficient. As expected, for the NG houses, the peak vs. mean loads are very close to those of the ALP loads. 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. For example, if a 'low-mean' ALP profile with a 'high-peak' is multiplied, the peak load of the 'multiplied' profile might become unrealistically large.

The peak-to-mean ratios are calculated for the 15-minute time-step houses using the values shown in Figure 5.8 and the results are shown in Table 5.1. The results are shown for the 1-minute time-step profiles as well.

Table 5.1 Range of peak and mean ratios for individual houses and two heating system types

		Peak-to-mean ratios		
		Min	Max	Average
n = 82, 15-minute time-step	ALP	5.4	28.5	14.1
	Whole-house (NG)	5.0	17.9	10.7
	Whole-house (ER)	3.7	5.6	4.8
	Whole-house (HP)	4.7	8.5	6.4
n = 20, 1-minute time-step	ALP	8.4	37.7	22.6
	Whole-house (NG)	7.8	24.5	16.3
	Whole-house (ER)	4.4	6.6	5.4
	Whole-house (HP)	5.4	9.3	7.5

As expected, the fluctuation is reduced dramatically when space heating becomes part of the load. For the ER and HP houses, the peak and mean loads increase by at least a factor of two (Figure 5.8), but the profile tends to fluctuate less frequently because the space heating loads are more consistent than the ALP loads.

Peak-to-mean ratios also tend to increase as the time-step is decreased and the ratios of profiles without heating (ALP and NG) increase by between 50% and 60% on average when the time-step is decreased from 15-minutes to 1-minute. For profiles with electric heating (ER and HP) the increase is only between 12% and 17%.

5.3.4.2 Communities

Lastly, this same evaluation is conducted for community loads (sum of the eighty-two 15-minute time-step whole-house loads and sum of twenty 1-minute time-step whole-house loads). The peak, mean, and peak-to-mean ratios are shown in Table 5.2.

Table 5.2 Peak and mean community ALP and whole-house loads for three heating system types

		Mean Load (kW)	Peak Load (kW)	Peak-to-mean Ratio
n = 82, 15-minute time-step	ALP	55.1	141.9	2.6
	Whole-house (NG)	73.8	225.7	3.6
	Whole-house (ER)	243.9	874.8	3.1
	Whole-house (HP)	182.1	891.3	4.9
n = 20, 1-minute time-step	ALP	11.7	51.0	4.4
	Whole-house (NG)	16.1	64.4	3.8
	Whole-house (ER)	58.0	219.6	4.0
	Whole-house (HP)	42.7	223.6	5.2

Comparing the values in Table 5.2 to those in Table 5.1, the peak-to-mean ratios of communities are generally less than those of individual loads. The reduction occurs for communities with all three heating system types, but is much more dramatic for the NG community. The rate of this reduction is of interest for community modeling so that the 'peak-to-mean' ratio can be used as an indicator that a sufficient number of unique occupant load profiles are being applied in a simulation. The gradual decrease of 'peak-to-mean' ratios with an increasing community size is shown for the ALP load and the whole-house load with the three heating system types in Figure 5.9.

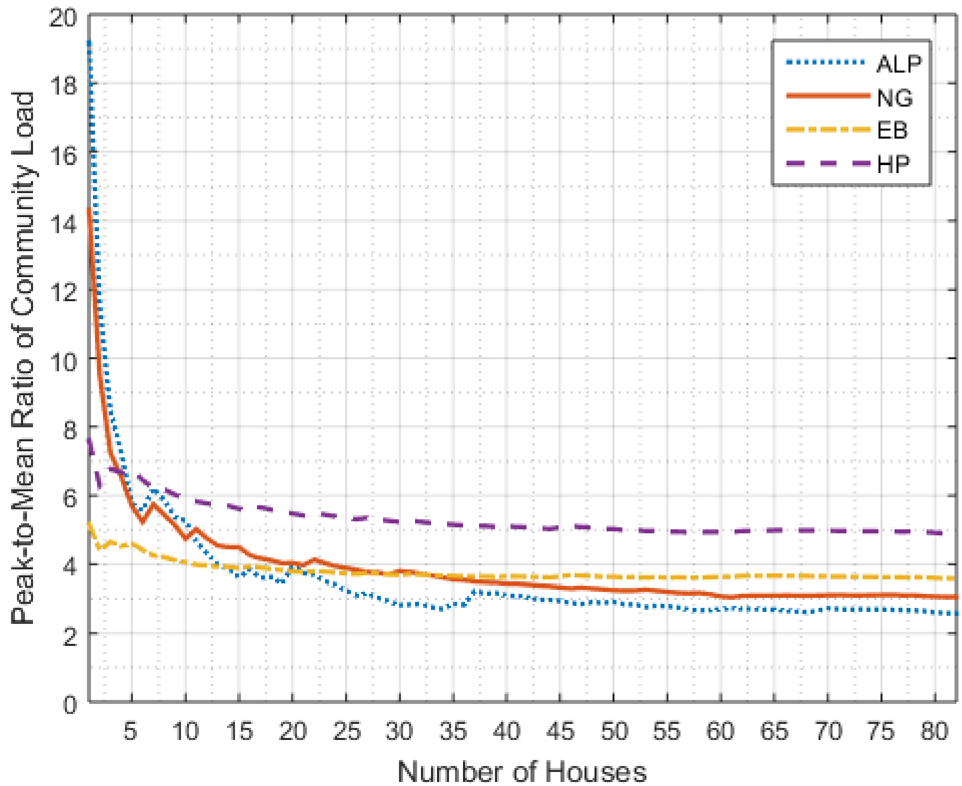

Figure 5.9 Peak-to-mean ratios with increasing size of community

From Figure 5.9, the peak-to-mean ratios for all load types initially decline rapidly but gradually stabilize. For the ALP load and the NG house loads which do not include space heating, 90-95% of the decline occurs within the addition of the first 15 houses. The same is true for ER and HP houses, but a less drastic decrease occurs overall. These results suggest that for the modeling of large communities, a smaller set of load profiles could be applied and repeated without drastically increasing the peak loads. Based on this metric, the use of a minimum of 15 ALP profiles is recommended before repeating profiles for demand modeling of larger communities.

5.4 Technical Application: Transformer Analysis

The load of smaller sub-groups of houses may be of interest to electric utility providers for the sizing of appropriate distribution equipment. For example, single phase polemounted transformers are commonly used in low density residential applications and can have a power range of between 25 to 100 kVA (ABB Power Technologies Division 2004). Rather than sizing a transformer, the community which the transformer services will instead need to be ‘sized’ to match the transformer capacity (i.e. the number of houses allocated to the transformer must be determined). A photo of a polemounted transformer in Halifax, Nova Scotia is shown in Figure 5.10.

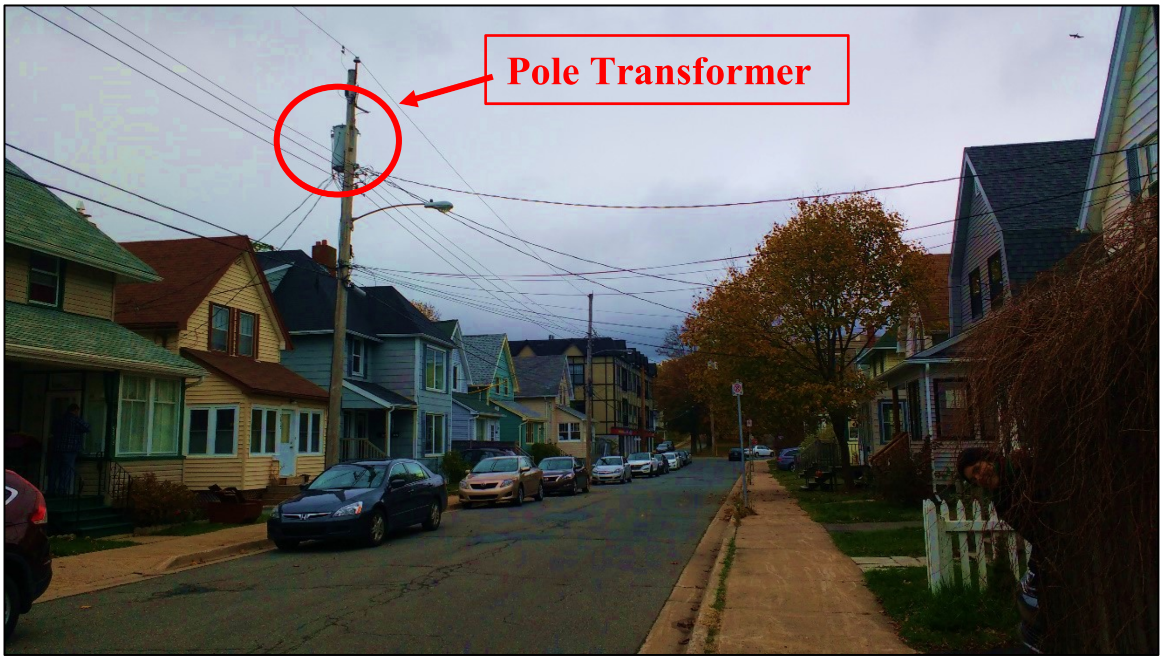

Figure 5.10 Single phase polemounted transformer

For this analysis, the simulated whole-house electricity load data at 15-minute time-steps is used and again, PV power generation is not taken into account. To determine the appropriate number of houses allocated to a polemounted transformer, the peak load is determined for combinations of houses within the 82 house dataset. An example of the aggregation of whole-house loads is shown in Figure 5.11, where 7 individual whole-house loads are plotted for a single winter day alongside their aggregated community load that has been scaled down by 7 to for comparison purposes. The aggregated whole-house loads that have been scaled down are much smoother than the individual whole-house loads.

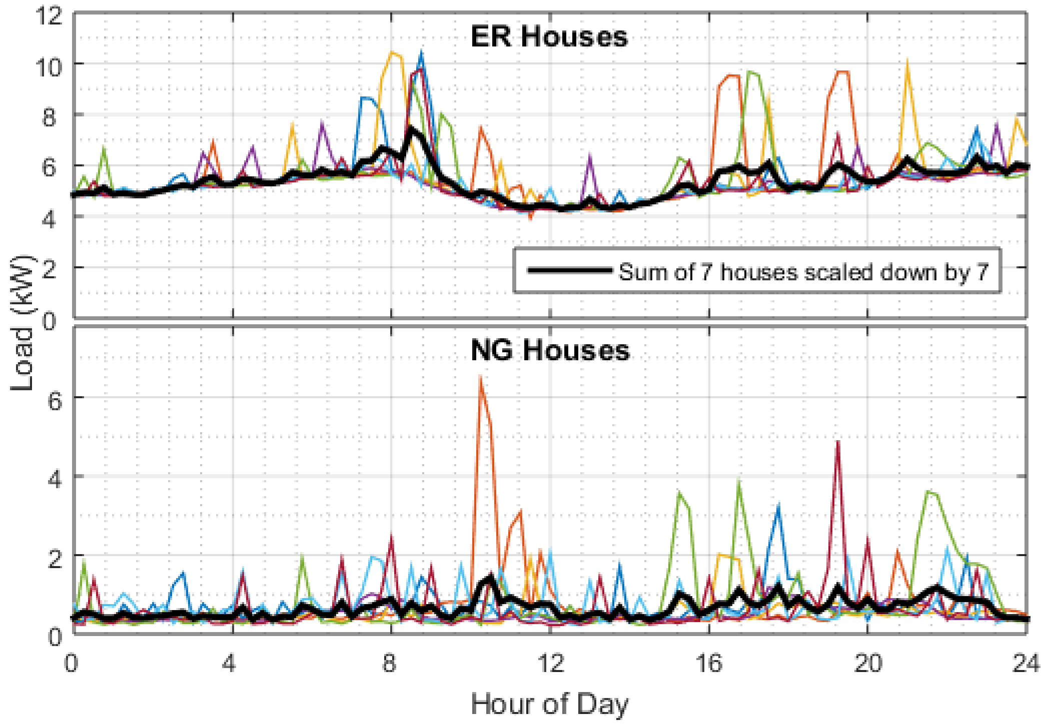

Figure 5.11 Individual whole-house loads for 7 ER and NG houses (thin colored lines) and their aggregated community load scaled by a factor of 7 (thick black line)

Combinations of 4 through 10 houses where created for each of the three heating system types to determine the effect of adding a houses to be serviced by a single transformer. However, not all possible combinations are tested, since there are too many to compute using computer software (there are over 35 billion combinations of 8 houses in a set of 82). Instead, 100,000 random combinations were generated for each community size (4-10) and each heating system type (NG, ER and HP). Figure 5.12 shows the distribution of peak loads the three heating system types for combinations of 7 houses.

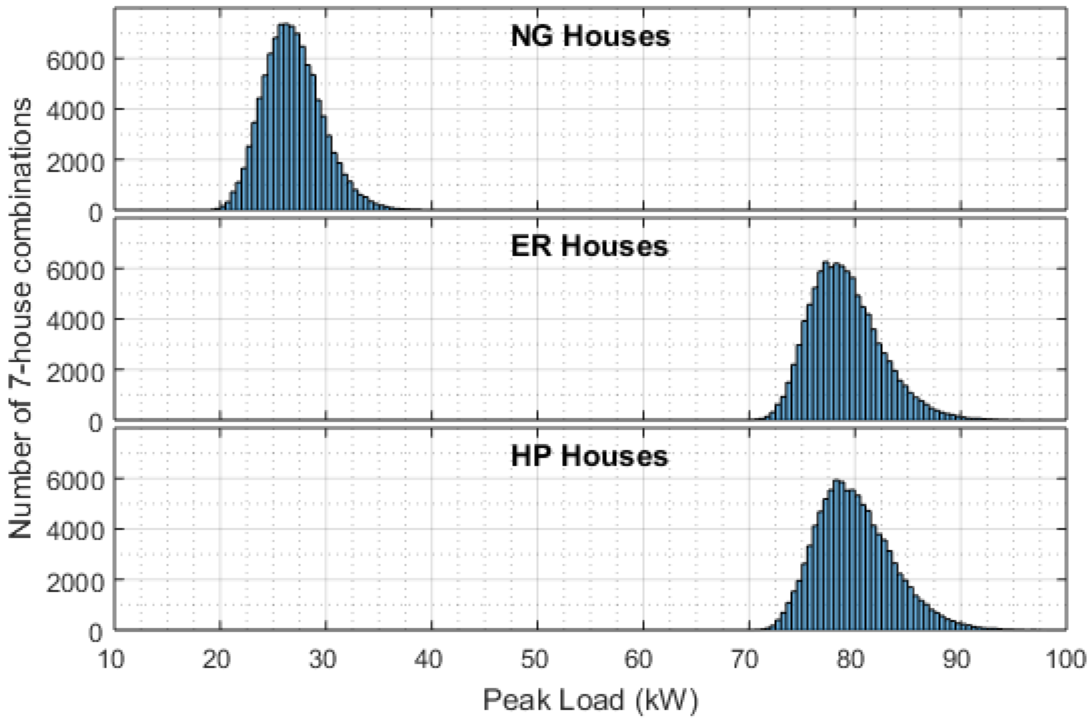

Figure 5.12 Distribution of peak loads for 100,000 random combinations of 7-house communities

For electrically heated homes in Figure 5.12, (ER and HP houses), the peak loads of these communities generally fall between 70 kW and 80 kW, however, some combinations produce peak loads which are approaching 100 kW. Assuming zero reactive power, this is the specified limit of some polemounted transformers. For NG houses, peak loads are much lower, ranging from approximately 15 kW to 40 kW. The results of all combinations are highlighted by Figure 5.13 which shows the mean, minimum and maximum peak loads out of 100,000 community load combinations for communities of 4 to 10 homes with three heating system types.

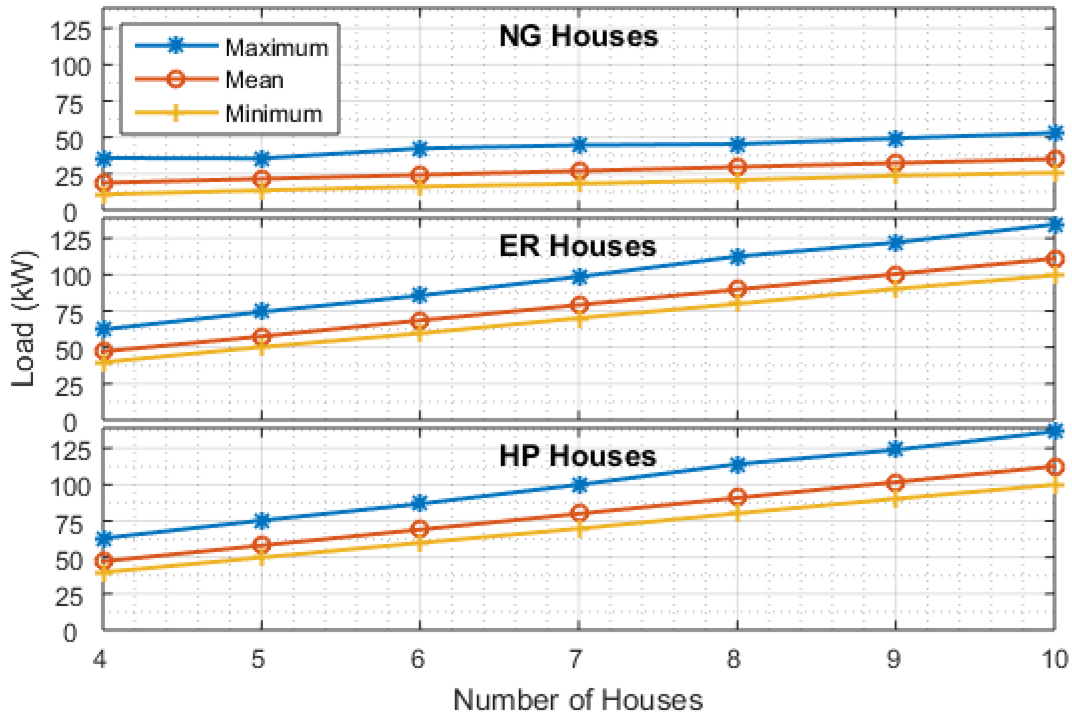

Figure 5.13 Mean, minimum and maximum peak loads for 100,000 community load combinations for communities of 4 to 10 homes with three heating system types

Figure 5.13 shows the peak community loads increasing linearly as houses are added to a community. The maximum peak loads for each distribution are represented by the blue asterisks. Based on these findings for this community, no more than 7 electrically heated houses should be allocated to a single 100 kVA transformer. However, for same community of non-electrically heated houses, up to 27 houses could be allocated to one transformer with a maximum peak load of 99 kW (not shown).

Using the measured occupant load data, a transformer sizing analysis could be completed for a proposed community that is under development. Building models and community configuration could be designed to better represent a real community.

5.5 Conclusions

This section demonstrates community simulation using the unique, measured occupant load profiles. A hypothetical, tract house community in a realistic configuration was modeled.

It was shown that community load profiles are much smoother than single house load profiles due to the variability of occupant consumption patterns. For community modeling, the 'peak-to-mean load' ratio is reduced when calculated at a community scale as compared to that of an individual house and this reduction is much more pronounced for communities that do not rely on electricity for space heating. For all heating system types, most of the reduction in 'peak-to-mean' load ratio occurs as a community reaches 15 houses in size.

This same effect was demonstrated when analysing the electrical grid imports and exports for individual houses and for communities with distributed solar PV generation. Non-coincident peaks in occupant loads resulted in a relatively stable community net-load compared to that of individual houses. Instead, climate factors such as cloud cover, have a much strong effect on community load fluctuations because all houses are subject to the same simultaneous changes in climate. This analysis could be elaborated further to evaluate the range storage and generation requirements to reduce community reliance on the electrical grid.

A variety of load profiles enable electrical utility equipment sizing because many permutations of house combinations can be tested to evaluate the chance of coincident peaks. An application was demonstrated by evaluating the number of houses that could be allocated to a 100 kVA polemounted transformer. It was determined, that for non-electrically heated homes, up to 27 homes could be serviced by one transformer with little chance that the peak community load would breach the upper limit. For electrically heated communities, peak loads could reach 100 kW with only 7 houses. These profiles and this analyses type could be completed for actual communities under development.

This section provides an analysis of a simple community scenario. This evaluation could be improved by incorporating other considerations to make the scenario more realistic. Some suggestions are:

- include external shading from trees and between buildings which significantly effect building energy consumption (Nikoofard et al. 2014b)
- account for a variety of building shapes and house orientations which would affect solar gains and PV system orientation

Chapter 6 Conclusion

6.1 Summary of Research

This research presents new datasets of residential household electricity load and DHW consumption measurements gathered from Canadian single detached homes and row houses. These include: (1) two cross Canada DHW consumption datasets from a municipal government pilot program and an industry research group, and (2) one new residential electricity load dataset from a Nova Scotia electrical utility. Also incorporated into this research is a previously published dataset of annual, sub-metered residential electricity load profiles from Ottawa, Ontario generated by an academic research group.

First, these datasets were analysed, compared, and rigorously examined for data quality issues. During this process, two novel methods have been developed to interpret measurements:

- a new method of interpreting erroneous DHW consumption measurements associated with consumer grade flow meters. The results of this finding can inform industry projects which rely on these flow meters for project validation (e.g. Halifax Regional Municipality's Solar City Program)
- a new method which makes use of seasonal and daily observations to identify homes from 'smart meter' datasets which do not rely on electricity for space heating, space cooling or DHW heating. This method can be applied to much larger datasets (such as 'smart meter' datasets) to generate additional ALP profiles.

Observations of occupant behavior were made. For DHW consumption, a strong positive correlation between consumption and occupancy was identified, as well as significant time-of-use variation between households. ALP energy use remains relatively consistent through the year, while DHW consumption tends to increase during the colder seasons. Both types of profiles demonstrate a diurnal consumption pattern, but DHW consumption tends to have a higher peak in the morning, while ALP energy consumption has a higher peak during the evening, particularly for the Ottawa dataset.

From the measured datasets, a new set of ALP and DHW profiles for use in building performance simulation has been generated, representing various time-of-use patterns and occupancy levels. These include 82 new annual DHW consumption profiles at a 1-minute time-steps and 62 new annual ALP profiles at 15-minute time-steps. It should be noted that while these profiles are based on measured data, the measurements have been interpreted and adjusted and some error in individual flow measurements has been introduced. However, the most important characteristic of the measured data remains: variability in occupant loads across households and within individual households. This measured variability makes these profiles valuable for building simulation applications.

The ALP and DHW profiles generated by this research have been demonstrated in both single household simulations and a community-scale simulation of up to 82 households. Two primary benefits of the new profiles were identified: (1) their high temporal resolution (1-minute) allows for the identification and analysis of electricity loads which typically run for less than this time-period (e.g. water heaters) and (2) the size of the dataset ensures variety in time-of-use patterns between the profiles enabling community modeling.

Several applications of the profiles have been identified and demonstrated:

- An evaluation of electric tankless water heaters was conducted and it was shown that for 5% of 82 households, this water heater type would provide a DHW water temperature lower than desired more than 10% of the time.
- An economic evaluation of TOD electricity pricing was evaluated against the electricity consumption of three heating system types for all homes and it was shown that under NSPI's existing TOD tariff, regular homeowners would spend less on electricity without changing their behaviour.
- The economic evaluation of TOD electricity pricing was extended to compare operating costs of tankless and tank water heaters. It was found that tank water

heaters consume more electricity on average and that DHW heating costs would decrease with both water heater types under the TOD tariff.

- A transformer sizing analysis was conducted for over 700,000 permutations of whole house profiles of 4 through 10 homes for sub communities of all three heating system types and it was shown that at approximately 7 houses, some community peak loads might exceed the specified limits of a 100 kVA polemounted transformer. For communities that do not rely on electric heating, many more houses can be supported by the same transformer.

6.1.1 Profile Limitations

Researchers should be aware of the origin and limitations of these profiles for building simulation application.

- The electricity profiles drepresent grid-connected single detached and row houses and would be limited in their applicability to off-grid housing where occupant behaviour and appliance ownership are limited by the finite availability of energy and they would not be applicable to multi-unit residential simulations which include different space types such as shared hallways and storage areas and difference outdoor lighting requirements. However, the DHW consumption profiles may still be valid for some multi-unit scenarios with in-unit clothes washing appliances.
- The profiles are limited by their statistical significance. Simulators should not overstate their representativeness of larger regions such as all of Nova Scotia or Ontario.

6.2 Recommendations

6.2.1 Future Occupant Load Measurements and Application of Methodology

The following are some suggestions for future work in this area:

1. As new occupant load data becomes available, the methods developed by this research should be further validated and developed using larger sources of measured data. The method developed in Chapter 3 to distinguish ALP profiles from larger

smart meter datasets could particularly benefit from further comparison with other high-resolution research grade datasets.

2. As smart meter datasets become available, the method developed in Chapter three can be applied to generate new sets of profiles that represent different regions. The characteristics of these regional datasets such as maximum peak-to-mean ratio should be evaluated and used to describe the ALP and whole-house loads of each region and distinctions can be made based on demographic classifications such as rural versus urban neighbourhoods or based on the varying electricity costs across provinces.

3. Smart meter recording intervals should be at time-steps of 5 minutes or less. ALP profiles at this time-step would enable the simulaton of various technologies while avoiding computational limitations of processing data at higher time-step resolutions.

4. Research grade data collection should be sub-metered a 1-minute time-steps or less to capture the behavior of DHW or electricity consuming devices such as solar or tankless water heaters.

5. Researchers seeking to measure occupant load data should seek to expand the database to include regional variety. This includes climate (see section 2.5.3.3 regarding seasonal variations in DHW consumption), demographics such as rural/urban communities, occupancy, and housetype (single detached vs. row housing), and factors such as energy pricing schemes (ie. TOD electricity pricing or even off-grid housing).

6. Community simulations could account for different physical scenarios. Some examples are to vary the heating system types and control strategies within a single community or to vary the community layout and add shading effects of trees and neighbouring buildings.

6.2.2 Application of Profiles

The new methodology and occupant load profiles should be applied in to real world contexts that can help with decision making. The following are suggestions:

1. Researchers and product designers can test their technologies over the range of occupant behavior contained within these datasets. For example, the performance of technologies such as solar DHW heaters and drain water heat recovery systems can be affected by variations in occupant loads.

2. Developers can run community scale simulations for design of low-energy communities. By applying these profiles, technical features of the community can be examined and optimized for entire communities, rather than for single houses.

3. Utilities can apply the profiles to evaluate technologies and tariffs across a range of user types to better understand the overall impact of new technologies on the utility grid. The example demonstrated in this research was that of tankless water heaters evaluated for energy consumption and demand volatility at a community scale and under standard and TOD electricity tariffs. Similar technologies that are relevant today are net-metered solar PV and distributed residential energy storage. Utilities may also be interested in studying grid interactive technologies, such as grid-controlled water heaters that can be controlled by grid operators for load-shifting, arbitrage, frequency regulation and grid stabilization.

4. Government agencies can incorporate these profiles into building simulation software. For example, NRCan has developed several software suites such as RETScreen and Hot2000 and the occupant load defaults can be informed based on the findings of Chapter 2 and Chapter 3. Furthermore, as NRCan develops archetype building energy models for the Canadian residential sector using time-step analysis tools such as EnergyPlus and OpenStudio, a selection of these profiles can be supplied with the models to represent a variety of user types.

5. Studies can be conducted to influence government agencies in developing energy efficiency and technology incentive programming. An example of this is the government mandated Efficiency Nova Scotia Corporation which has been delivering energy efficiency programming in Nova Scotia for over a decade. Their programming has primarily focused on reducing aggregate energy consumption rather than time-step electricity demand. For this type of programming to continue, there will be increasing pressure to align electricity demand savings with particular generation or occupant load patterns so that generation capacity can also be reduced.

References

Adye, K., Pearre, N., & Swan, L. (2014). Solar city on-site assessment summary report: House characteristics, and water and energy savings. For Halifax Regional Municipality. Halifax, Nova Scotia. 27 pages.

ABB Power Technologies Division. (2004). Transformer handbook. Zurich, Switzerland: ABB.

American Society of Heating, Refrigerating and Air-Conditioning Engineers Inc. (ASHRAE), (2011). Service water heating: Hot water requirements and storage equipment sizing. In Mark S. Owen (Ed.), *ASHRAE handbook: HVAC applications (pp. 50.1-50.15)*. Atlanta, GA: American Society of Heating, Refrigerating and Air-Conditioning Engineers, Inc.

Armstrong, M. M., Swinton, M. C., Ribberink, H., Beausoleil-Morrison, I., & Millette, J. (2009). Synthetically derived profiles for representing occupant-driven electric loads in Canadian housing. *Journal of Building Performance Simulation*, 2(1), 15-30. doi: http://doi.org/10.1080/19401490802706653

Asaee, S. R., Ugursal, V. I., & Beausoleil-Morrison, I. (2015). An investigation of the techno-economic impact of internal combustion engine based cogeneration systems on the energy requirements and greenhouse gas emissions of the Canadian housing stock. Applied Thermal Engineering, 87, 505-518. doi:http://dx.doi.org.ezproxy.library.dal.ca/10.1016/j.applthermaleng.2015.05.031

Asaee, S. R., Ugursal, V. I., & Beausoleil-Morrison, I. (2016). Techno-economic study of solar combisystem retrofit in the Canadian housing stock. Solar Energy, 125, 426-443. doi:http://dx.doi.org.ezproxy.library.dal.ca/10.1016/j.solener.2015.12.037

Asaee, S. R., Ugursal, V. I., & Beausoleil-Morrison, I. (2017). Techno-economic feasibility evaluation of air to water heat pump retrofit in the Canadian housing stock. Applied Thermal Engineering, 111, 936-949. doi:http://dx.doi.org.ezproxy.library.dal.ca/10.1016/j.applthermaleng.2016.09.117

Aydinalp-Koksal, M., Rowlands, I. H., & Parker, P. (2015). Energy, cost, and emission end-use profiles of homes: An Ontario (Canada) case study. *Applied Energy*, 142(0), 303-316. doi: http://dx.doi.org/10.1016/j.apenergy.2014.12.077

Basu, K., Debusschere, V., Douzal-Chouakria, A., & Bacha, S. (2015). Time series distance-based methods for non-intrusive load monitoring in residential buildings. *Energy and Buildings*, 96, 109-117. doi:http://dx.doi.org/10.1016/j.enbuild.2015.03.021

Becker, B. R., & Stogsdill, K. E. (1990). Development of a hot water use data base. Paper presented at the 1990 Annual Meeting of the American Society of Heating, Refrigerating and Air-Conditioning Engineers, Technical and Symposium Papers, June 10, 1990 - June 13, pp. 422-427.

CANMET Energy Technology Center (CETC). (2008). *HOT2000* (10.51st ed.). Ottawa: Natural Resources Canada. Retrieved May 4, 2015, 2015, from: https://www.nrcan.gc.ca/energy/software-tools/7421

CANMET Energy Technology Center (CETC). (2013). RETScreen (4th ed.). Ottawa: RETScreen International Natural Resources Canada. Retrieved May 4, 2015, 2015, from: http://www.retscreen.net/ang/software_and_data.php

CANMET Energy Technology Center (CETC). (2016a). HOT2000 (v11.2b86). Ottawa: Natural Resources Canada. Retrieved March 29, 2016, from: http://www.nrcan.gc.ca/energy/efficiency/housing/home-improvements/17725

CANMET Energy Technology Center (CETC). (2016b). RETScreen Expert. Ottawa: RETScreen International Natural Resources Canada. Retrieved October 26, 2016, from: http://www.nrcan.gc.ca/energy/software-tools/7465

Chen, V. L., Delmas, M. A., Kaiser, W. J., & Locke, S. L. (2015). What can we learn from high-frequency appliance-level energy metering? Results from a field experiment. *Energy Policy*, 77, 164-175. doi:http://dx.doi.org/10.1016/j.enpol.2014.11.021

Edwards, S., Beausoleil-Morrison, I., & Laperrière, A. (2015). Representative hot water draw profiles at high temporal resolution for simulating the performance of solar thermal systems. *Solar Energy, 111*, 43-52. doi:http://dx.doi.org.ezproxy.library.dal.ca/10.1016/j.solener.2014.10.026

Efficiency Nova Scotia (2015). Product installation. Retrieved February 12, 2015, from http://www.efficiencyns.ca/energy-solutions/home-installation-solutions/

EnergyPlus. (2015). EnergyPlus Documentation, v8.4.0, Engineering Reference, The Reference to EnergyPlus Calculations. University of Illinois & the Ernest Orlando Lawrence Berkeley National Laboratory.

Evarts, J. C., & Swan, L. G. (2013). Domestic hot water consumption estimates for solar thermal system sizing. *Energy and Buildings, 58*, 58-65. doi:http://dx.doi.org.ezproxy.library.dal.ca/10.1016/j.enbuild.2012.11.020

Firth, S., Lomas, K., Wright, A., & Wall, R. (2008). Identifying trends in the use of domestic appliances from household electricity consumption measurements. *Energy and Buildings*, 40(5), 926-936. doi:http://dx.doi.org/10.1016/j.enbuild.2007.07.005

Fung, A. S., & Gill, G. S. (2011). Energy and environmental analysis of residential hot water systems: A study for Ontario, Canada. *ASHRAE Transactions*, 117. (PART 2) pp. 506-520.

George, D., Pearre, N.S., Swan, L.G. 2015. High resolution measured domestic hot water consumption of Canadian homes. *Energy and Buildings*, 109, 304-315. doi:http://dx.doi.org/10.1016/j.enbuild.2015.09.067

George, D. and Swan, L. G. (2016). A method for distinguishing appliance, lighting and plug load profiles from electricity 'smart meter' datasets. *Energy and Buildings*. In press. doi:10.1016/j.enbuild.2016.10.048

Government of Canada (2015). Daily data report for 2014: Climate ID: 8205092 Retrieved 05/05, 2015, from http://climate.weather.gc.ca/climateData/dailydata_e.html?timeframe=2&Prov=NS%20%20&StationID=47187&dlyRange=2008-07-02|2015-05-04&Year=2014&Month=5&Day=4

Hachem, C., Athienitis, A., & Fazio, P. (2012). Evaluation of energy supply and demand in solar neighborhood. *Energy and Buildings, 49*, 335-347. doi:http://dx.doi.org/10.1016/j.enbuild.2012.02.021

Hachem, C., Fazio, P., & Athienitis, A. (2013). Solar optimized residential neighborhoods: Evaluation and design methodology. *Solar Energy, 95*, 42-64. doi:http://dx.doi.org/10.1016/j.solener.2013.06.002

Hachem, C. (2015). Design of a base case mixed-use community and its energy performance. *Energy Procedia, 78*, 663-668. doi:http://dx.doi.org/10.1016/j.egypro.2015.11.056

Hachem-Vermette, C., Cubi, E., & Bergerson, J. (2015). Energy performance of a solar mixed-use community. *Sustainable Cities and Society*, doi:http://dx.doi.org/10.1016/j.scs.2015.08.002

Hachem, C. (2016). Impact of neighborhood design on energy performance and GHG emissions. *Applied Energy, 177*, 422-434. doi:http://dx.doi.org/10.1016/j.apenergy.2016.05.117

Han, Y., Beausoleil-Morrison, I., & Wang, X. (2015). Increasing the installation capacity of PV with PEMFC backup within a residential community. *Energy Procedia, 78*, 675-680. doi:http://dx.doi.org.ezproxy.library.dal.ca/10.1016/j.egypro.2015.11.060

Hendron, R., & Burch, J. (2007). Development of standardized domestic hot water event schedules for residential buildings. *Proceedings of the ASME 2007 Energy Sustainability Conference Long Beach*, California, USA. pp. 531-539.

Hendron, R., & Engebrecht, C. (2010). Building America House Simulation Protocols, National Renewable Energy Laboratory.

Home Depot of Canada Inc. (2016). Advantage 27 KW whole home electric tankless water heater. Retrieved October 21, 2016, from https://www.homedepot.ca/en/home/p.advantage-27-kw-whole-home-electric-tankless-water-heater.1000841437.html

International Code Council (ICC). (2012). International Energy Conservation Code. Washington, DC: International Code Council.

Johnson, G., & Beausoleil-Morrison, I. (2016). Electrical-end-use data from 23 houses sample each minute for simulating micro-generation systems. *Applied Thermal Engineering*, doi:http://dx.doi.org/10.1016/j.applthermaleng.2016.07.133

Jordan, U., & Vajen, K. (2001a). Realistic domestic hot-water profiles in different time scales. Univ Marburg, Germany: International Energy Agency – Solar Heating and Cooling Program, Task 26.

Jordan, U., & Vajen, K. (2001b). Influence of the DHW load profile on the fractional energy savings: A case study of a solar combi-system with TRNSYS simulations. *Solar Energy*, 69, Supplement 6, 197-208.

Kersting, W., H. (2002). Distribution system modeling and analysis. Boca Raton, Florida, U.S.A.: CRC Press.

Knight, I., Kreutzer, N., Manning, M., Swinton, M., & Hajo, R. (2007). European and Canadian non-HVAC electric and DHW load profiles for use in simulating the performance of residential cogeneration systems. A report of subtask A of FC+COGEN-SIM the simulation of building-integrated fuel cell and other cogeneration systems. Ottawa, Canada: International Energy Agency Energy Conservation in Buildings & Community Systems Programme, Natural Resources Canada.

Leadbetter, J., & Swan, L. (2012). Battery storage system for residential electricity peak demand shaving. *Energy and Buildings*, 55, 685-692. doi:http://dx.doi.org/10.1016/j.enbuild.2012.09.035

Lee, S., Whaley, D., & Saman, W. (2014). Electricity demand profile of Australian low energy houses. *Energy Procedia*, 62, 91-100. doi:http://dx.doi.org/10.1016/j.egypro.2014.12.370

Malone, P., & Malone, S. (2013). Web energy logger. Retrieved February 07, 2015, from www.welserver.com

Naspolini, H. F., & Rüther, R. (2016). The effect of measurement time resolution on the peak time power demand reduction potential of domestic solar hot water systems. *Renewable Energy*, 88, 325-332. doi:http://dx.doi.org/10.1016/j.renene.2015.11.046

National Energy Board (NEB). (2013). Canada's Energy Future 2013: Energy supply and demand projections to 2035. Retrieved 02/17, 2016, from https://www.neb-one.gc.ca/nrg/ntgrtd/ftr/2013/2013nrgftr-eng.pdf

Natural Resources Canada (NRCan) (2012). Comprehensive energy use database, 1990 to 2012. Retrieved from http://oee.nrcan.gc.ca/corporate/statistics/neud/dpa/menus/trends/comprehensive_tables/list.cfm

Natural Resources Canada (NRCan). (2013). Survey of household energy use 2011 - detailed statistical report. Retrieved from http://oee.nrcan.gc.ca/publications/statistics/sheu/2011/pdf/sheu2011.pdf

Natural Resources Canada (NRCan). (2014a). Energy use handbook tables. Retrieved 05/06, 2015, from http://oee.nrcan.gc.ca/corporate/statistics/neud/dpa/menus/trends/handbook/tables.cfm

Natural Resources Canada (NRCan). (2014b). Halifax regional municipality solar city pilot program. Retrieved February 12, 2015, from http://www.retscreen.net/ang/halifax_regional_municipality_solar_city_pilot_program.php

Natural Resources Canada (NRCan). (2015). Integrating renewables and conservation measures in a net-zero energy low-rise residential subdivision. Retrieved 02/17, 2016, from https://www.nrcan.gc.ca/energy/funding/current-funding-programs/eii/16140

Nikoofard, S., Ismet Ugursal, V., & Beausoleil-Morrison, I. (2014a). An investigation of the technoeconomic feasibility of solar domestic hot water heating for the Canadian housing stock. Solar Energy, 101(0), 308-320. doi:http://dx.doi.org/10.1016/j.solener.2014.01.001

Nikoofard, S., Ismet Ugursal, V., & Beausoleil-Morrison, I. (2014b). Technoeconomic assessment of the impact of window shading retrofits on the heating and cooling energy consumption and GHG emissions of the Canadian housing stock. *Energy and Buildings, 69*(0), 354-366. doi:http://dx.doi.org/10.1016/j.enbuild.2013.11.023

Nova Scotia Power Incorporated (NSPI). (2016). *Electricity rates and regulations.* Retrieved 10/20, 2016, from http://www.nspower.ca/en/home/about-us/electricity-rates-and-regulations/default.aspx

OMEGA Engineering Inc. (2015). Water Meters for Totalization and Rate Indication with Pulse Output. Retrieved August 13, 2015, from http://www.omega.com/pptst/FTB8000B.html

Onset Computer Corporation. (n.d.) Powerful web-based access to HOBO data loggers. Retrieved 11/07, 2016, from https://www.hobolink.com/

Onset Computer Corporation. (2014). Hobo U30 Station NRC User's Guide. Retrieved August 13, 2015, from http://www.onsetcomp.com/files/manual_pdfs/11866-H-U30-NRC-Manual.pdf

Parekh, A., Wang, P., & Strack, T. (2012). Survey results of user-dependant electricity loads in Canadian homes. ACEEE Summer Study on Energy Efficiency in Buildings.

Perlman, M., & Mills, B. E. (1985). Development of residential hot water use patterns. *ASHRAE Transactions*, 91(2A), 657-679.

Richardson, I., Thomson, M., Infield, D., & Delahunty, A. (2009). Domestic lighting: A high-resolution energy demand model. Energy and Buildings, 41(7), 781-789. doi:http://dx.doi.org.ezproxy.library.dal.ca/10.1016/j.enbuild.2009.02.010

Richardson, I., Thomson, M., Infield, D., & Clifford, C. (2010). Domestic electricity use: A high-resolution energy demand model. Energy and Buildings, 42(10), 1878-1887. doi:http://dx.doi.org.ezproxy.library.dal.ca/10.1016/j.enbuild.2010.05.023

Saldanha, N., & Beausoleil-Morrison, I. (2012). Measured end-use electric load profiles for 12 Canadian houses at high temporal resolution. *Energy and Buildings*, 49, 519-530. doi: http://dx.doi.org/10.1016/j.enbuild.2012.02.050

Spur, R., Fiala, D., Nevrala, D., & Probert, D. (2006). Influence of the domestic hot-water daily draw-off profile on the performance of a hot-water store. *Applied Energy*, 83(7), 749-773.

Statistics Canada. (2013a). Household size, by province and territory (2011 census) (Newfoundland and Labrador, Prince Edward Island, Nova Scotia). Retrieved 02/27, 2015, from http://www.statcan.gc.ca/tables-tableaux/sum-som/l01/cst01/famil53a-eng.htm

Statistics Canada. (2013b). Private households by structural type of dwelling, by province and territory (2011 census) (Newfoundland and Labrador, Prince Edward Island, Nova Scotia). Retrieved 04/04, 2016, from http://www.statcan.gc.ca/tables-tableaux/sum-som/l01/cst01/famil55a-eng.htm

Statistics Canada. (2013c). Private households by structural type of dwelling, by census metropolitan area (2011 census) (Ottawa–Gatineau, Kingston, Peterborough, Oshawa, Toronto). Retrieved 04/07, 2016, from http://www.statcan.gc.ca/tables-tableaux/sum-som/l01/cst01/famil124c-eng.htm

Statistics Canada. (2015). Dual-earning families as a proportion of couple families with a least one child under 16 years of age, by region or province, 1976 and 2014. Retrieved 04/04, 2016, from http://www.statcan.gc.ca/daily-quotidien/150624/cg-a001-eng.htm

Swan, L. G., Ugursal, V. I., Beausoleil-Morrison, I. (2009). A database of house descriptions representative of the Canadian housing stock for coupling to building energy performance simulation. *Journal of Building Performance Simulation*, 2(2), 75-84.

Swan, L. G., Ugursal, V. I., & Beausoleil-Morrison, I. (2011). Occupant related household energy consumption in Canada: Estimation using a bottom-up neural-network technique. *Energy and Buildings*, 43(2–3), 326-337.

Swan, L. G., Ugursal, V. I., & Beausoleil-Morrison, I. (2013). Hybrid residential end-use energy and greenhouse gas emissions model – development and verification for Canada. *Journal of Building Performance Simulation*, 6(1), 1-23.

Taylor, Z., Mendon, V., Fernandez, N. (2015). Method for Evaluating Cost-Effectiveness of Residential Energy Code Changes. Springfield, VA: U.S. Department of Energy.

Thomas, M., Hayden, A. C. S., Ghiricociu, O., Cane, R. L. D., & Gagnon, R. (2011). A new study of hot-water use in Canada. Paper presented at the 2011 ASHRAE Winter Conference, January 29 - February 2, 2011, 117. pp. 673-682.

Ultisolar Group (2010). USC-HS43TB big hall flow sensor 2-45L/min BSP3/4" 60mm. Retrieved 02/23, 2015, from http://www.ultisolar.com/post/USC-HS43TB-Big-Hall-Flow-Sensor-2-45L-min-BSP3-4-60mm.html

Water Heater Hub. (2016). Tankless vs tank type water heater. Retrieved 11/15, 2016, from https://www.waterheaterhub.com/tankless-vs-tank-type-water-heater/

Wills, A., Beausoleil-Morrison, I. & Ugursal, V. I. (2016). Evaluation of source net-zero performance for residential community-scale retrofit photovoltaic systems in Canadian locations. Proceedings of the eSim 2016 Building Performance Simulation Conference, Hamilton, Ontario, Canada.

Zeifman, M., & Roth, K. (2011). Nonintrusive appliance load monitoring: Review and outlook. *IEEE Transactions on Consumer Electronics*, 57(1), 76-84. doi:10.1109/TCE.2011.5735484

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