Energy and Buildings 139 (2017) 326–339

Contents lists available at ScienceDirect

Energy and Buildings

journal homepage: www.elsevier.com/locate/enbuild

Aggregated and disaggregated correlations of household electricity consumption with time-of-use shifting and conservation

Ivan Kantor*, Ian H. Rowlands, Paul Parker

University of Waterloo, 200 University Avenue West, Waterloo, Ontario, N2L 3G1, Canada

ARTICLE INFO

Article history:
Received 18 April 2016
Received in revised form 1 November 2016
Accepted 17 December 2016
Available online 29 December 2016

Keywords:
Residential
Electricity
Policy
Buildings
Disaggregated
Discretionary
Conservation
Load-shifting
Ontario
Canada
Demand management

ABSTRACT

Conservation and demand management of electricity is actively being pursued within the province of Ontario, Canada in an attempt to avoid new facility construction, manage costs, reduce emissions and also relieve stress on the electricity grid. The research presented here examines the consumption patterns of residential householders when provided with near-real-time, disaggregated electricity consumption data. Correlation coefficients are calculated between grouped appliance consumption and overall load-shifting or conservation patterns. Results show that householders who shift loads to off-peak do so by modifying consumption patterns of active loads in specific consumption categories. Conservation behavior is found in two of 18 households and is correlated to the consumption pattern of air conditioning units, major and discretionary loads. Policy focusing on conservation and demand management should therefore be specifically developed to stimulate the desired response from residential customers.

1. Introduction

The level of electricity consumption in developed nations as well as the timing of the consumption has become increasingly important to utility companies, governments and society. Exceeding the capacity of the electrical system has serious implications for grid stability which affects commercial, industrial and residential sectors. Such a situation in the province of Ontario, Canada in August 2003 proved that measures needed to be introduced to curb the escalating use of electricity and also to shift the times at which electricity was being consumed [1]. The government of Ontario introduced conservation goals to reduce demand and established time-of-use pricing to promote the use of electricity during off-peak periods when generation of electricity is less expensive and capacity is available [2]. Government programs have explored several routes to achieve these goals such as distributed small-scale generation supported by feed-in tariffs and conservation and demand management incentives during peak demand periods [3].

Generation and supply of electricity within Ontario, Canada is managed largely by government-controlled bodies, thus the provincial government has a large stake in effectively managing electricity generation, transmission and consumption within Ontario [3]. Financially, it is in the interest of utilities, and therefore the provincial government and consumers, to encourage conservation of electricity and peak demand shifting to avoid the burden of constructing new generation and transmission facilities. Householders also benefit financially from conservation and load-shifting efforts due to smart-metering being installed in the study region.

To date, results from changing rate structures have been mixed [4] considering aggregate household consumption. Therefore, this work attempts to identify appliance groups which are correlated with household conservation or load shifting according to existing grouping methods defined in the literature while proposing two new approaches to appliance consumption grouping. Additionally, this study uses electricity consumption disaggregated at the circuit level which provides a distinct advantage in identifying the consumption of each appliance group. The goal of this study is to show which groups of appliances are responsible for observed shifts in usage times or conservation and thus the most likely areas to find success from conservation programs initiated by utility providers or governments.

* Corresponding author.
E-mail address: ikantor@uwaterloo.ca (I. Kantor).

http://dx.doi.org/10.1016/j.enbuild.2016.12.054
0378-7788/

To achieve these results, this article is divided into six major sections. Following this brief introduction, the second section sets the context by placing our investigation into the broader literature, showing how we both build upon existing knowledge and have the potential to contribute to the same. The particular case-study is also introduced with a description of the broader setting (the electricity system in the Canadian province of Ontario) and the specific project (involving households in the town of Milton, Ontario). In the third section, attention turns to the electricity monitoring systems in the households, as well as the ways in which the data collected by those systems were prepared. The methodology is presented in the fourth section, and the results – and accompanying discussion – follow in the fifth section. Finally, conclusions – including both research and policy recommendations – are offered in the sixth section.

2. Background and contributions

To establish the context for our detailed investigation into a Canadian case-study, the broader literature which is drawn from and contributed to is reviewed; following this, the introduction to the electricity system in the study location is presented. The following section describes the state of research in this field as a short review of the pertinent literature. As the intention of this research is also to contribute to appliance grouping methods, two of these existing methods are also presented as they are applied in this research, adapted for the context of the study region.

2.1. State of the art

Research into the ways in which – and the extent to which – interventions providing householders with more electricity information have changed consumption patterns has been carried out for more than a decade. For instance, Abrahamse et al. conducted a review of intervention literature as it pertained to electricity consumption in 2005 before proceeding to conduct an assessment of 189 households over a period of five months in 2007 [5,6]. Both studies conducted by Abrahamse et al. examined the psychology of electricity consumption and specifically attempted to evaluate the success of different types of intervention on householder behavior. The review of literature yielded conflicting or imperfect conclusions and thus did not solidify the mechanisms by which interventions could impact householder behavior; however, the authors maintained that there is evidence of behavioral modification. The authors concluded that goal-setting is an important feature and that a focus specifically on load-shifting or total conservation will have an impact on the specified area but not necessarily provide any side benefits in the other domain. The authors also noted that there are conflicting and often equivocal results from studies of this nature and that they can be very difficult to interpret properly. In the subsequent study in 2007, Abrahamse et al. found that reduction in the overall usage of energy (not specifically electricity) could be encouraged by providing a multitude of interventions in the form of feedback, goal setting and information tailored to individual households.

Moreover, Firth et al. [7] studied 72 houses in the United Kingdom and found that electrical consumption increased over time and had several reasonable explanations for this. The authors identified that these homes were newly-constructed or recently acquired and thus it was likely that householders were 'growing into' the homes, purchasing additional electronics and appliances to fulfil their needs. Firth et al. also noted that the households in the study increased their electrical consumption at almost four times the rate of the national average and suggested further monitoring of the households to assess whether this trend would continue. In addition, the authors noted that access to disaggregated data would be an asset for continuing to assess the consumption patterns of householders in the UK and that further projects would be continuing to improve on the methods and results presented. This study is a representative example of the direction of research in consumption analysis in the realm of conservation, demand management, and householder interaction with electricity management systems. The Smart Metering Early Learning Project in the UK states that "We know remarkably little about just where savings and more durable reductions are made through changes in behavior and routines, though a rough order of priority seems to run from lighting through the more discretionary household appliances to space- and water-heating" [8]. Both of these projects have cited that an approach to the problem using disaggregated data is essential to better understand the complex nature of the situation.

In another review, Faruqui et al. concluded that in-home displays reduced electrical consumption by 3–13% in a survey of 12 pilot programs throughout the world with several in North America [9]. Access to disaggregated data is proposed to have a higher potential for reducing consumption than the household aggregate measurement. This theory is validated by a small Japanese study by Ueno et al. [10] but also contrasts the findings from research by Firth et al. [7].

Ueno et al. installed monitoring equipment for household appliances in nine newly-constructed houses in Japan [10]. The small sample size and age of dwellings makes this a relevant Japanese analog to the research presented here. Ueno et al. found that eight of the houses reduced consumption by 9% on average and that electrical loading of the television in these eight houses had been reduced by 5% which was cited as a major finding. The study does not attempt to assess the load-shifting impacts of the equipment and focused solely on the overall consumption of the household.

Dent et al. [11] attempted to utilize a clustering method for identifying the variability in household electricity consumption for 4-hour evening periods of 16:00 to 20:00 h daily in 180 UK households. The purpose of the research presented by Dent et al. was to mathematically decipher the willingness of householders to alter their electricity consumption behaviors to find which households should be targeted for conservation programs. Despite the findings, the authors did not attempt to engage the householders in conservation programs, the goal being only to identify potential candidates for such.

Several studies have shown results that in-home energy displays lead to reductions in electrical consumption [9,10,12–15]. Many additional studies focus on methodology to disaggregate household electricity consumption to identify appliance trends and consumption patterns which are otherwise buried within the aggregate consumption of a household meter [7,16–18].

This review of the literature leads to three important observations; firstly, the need for household electricity consumption disaggregated by appliance is required for better understanding the usage patterns within households and where householders change consumption behavior. Secondly, many studies in electrical conservation take place over short periods of time and cannot adequately assess the persistence of conservation efforts through time [19]. Finally, previous research suggests that appliance groups are correlated with conservation but no research was identified that compares different grouping methods. Previous researchers have proposed several ways to group appliances, two have been selected for this study and two new methods are also proposed as discussed in Section 2.2.

2.1.1. UK DECADE grouping

The first grouping of appliances is based on the Domestic Equipment and Carbon Dioxide Emissions (DECADE) program in the United Kingdom [20,21]. This method categorizes appliances based on whether they are for lighting, refrigeration, cooking, or fall into categories of brown or wet uses. The lighting and refrigeration categories account for electric lighting and refrigeration appliances, respectively. Cooking appliances include electric stoves, ovens, microwaves or other appliances used for preparing food. Brown uses include televisions, media centres, home offices, computers, smoke detectors and outlets for tools or other electronics, etc. Wet uses include dishwashers, clothes washers/dryers, sump pumps and water heaters. An additional category which is added for the North American context is space conditioning. While the UK classification does not deal directly with this type of electricity use, it is a major part of North American electricity use. This added category includes items such as air conditioning, furnace fan and any other heating/cooling appliance specifically for conditioning the temperature in a dwelling.

2.1.2. User interaction grouping

This method, proposed by Firth et al. [7], groups electrical loads into the categories of continuous, standby, cold and active uses. This grouping method is supported in further studies on the UK Carbon Reduction in Buildings (CaRB) program [22]. Grouping electrical uses in this way is indicative of how householders interact with those uses. Continuous uses are defined as loads that have a small but constant load and typically there is little interaction between users and the load. Examples of continuous loads are presented by Firth et al. as clocks, alarm systems, internet modems/routers, etc. Standby loads are differentiated from continuous loads when the householder interacts with them. The electrical consumption of standby loads when inactive (in standby mode) is typically small and would be similar to continuous loads, but have the capacity to draw considerably higher loads when in active use. Examples of this type of appliance would be media centres, computers, televisions, etc. The third category in this group is cold appliances and includes appliances intended for refrigeration, typically a refrigerator, freezer or a combination of the two. These appliances have non-zero loads when not in use (standby mode) and have significantly higher consumption when the refrigeration equipment is switched on (active mode) but this change is automatic and not influenced by the householder. The automatic nature of the increased load and the use of this electrical energy differentiate cold appliances from standby appliances. The final category in this grouping system is active uses. This describes loads that have zero consumption when not in use but typically very high consumption when in use. Examples of this would include lighting, electric stoves, laundry machines, dishwashers, etc. The household actively chooses when to utilize these systems but when not in use, they are non-consumers.

2.2. Contributions

Recommendations from literature point to several needs which are addressed in this research. Firstly, this research explores the conservation and demand-shifting impacts of householder access to near-real-time (five minute delay) electricity consumption data, already disaggregated by appliance. This research also answers a clear call from the existing literature to identify which loads are used by householders and which are responsible for conserving or shifting consumption in a household. Additionally, two new classification systems of electrical usage are presented in addition to existing grouping methods and load-aggregation is conducted in a variety of ways to assess collective contributions to shifting and conservation of particular electrical loads. Additionally, the geographical context of Ontario, Canada has not been studied to a noticeable degree in the current body of research on this topic but is one of the only mandatory time-of-use (ToU)-rate participation jurisdictions in the world and thus presents a very interesting case. This research could thus be applied by policy-makers and electrical generators in this jurisdiction to encourage conservation in the most appropriate areas according to appliance grouping shown herein while also providing guidelines for other research in this area throughout the globe.

Building on the work of Abrahamse et al. [5,6], the intervention considered in this current work is the installation of household monitoring equipment. Access to near-real-time electricity consumption feedback has been shown to be critical to reducing consumption of electricity. The context for the study included an existing time-of-use pricing system to encourage peak shifting with smart metering devices installed at each household between 2005 and 2010. Peak-shifting in this study refers to shifting loads to off-peak periods which occur on weekdays between 19:00 and 7:00 h as well as on holidays and weekends; full details of the ToU pricing periods and costs can be found in our previous work [23]. Additional interventions were introduced as part of the project such as e-mail prompts, but the primary focus of this study is the impact of appliance-level consumption when householders are given access to near-real-time consumption data (five minute delay).

The electricity usage clustering method developed in Dent et al. [11] focuses on finding the flexibility of householder electricity consumption based on variations in the usage patterns of households. The research presented here examines appliance usage data in various logical groups to determine what appliances are responsible for such flexibility. This is determined by assessing usage data for the households that have modified consumption patterns in a desirable way and investigating the appliance-specific modifications that prompted load shifting or overall household electrical conservation.

Speculation by the Smart Meter Early Learning Program in the UK suggests that conservation efforts of households follow a progression of effort from lighting to discretionary appliances to space- and water-heating but also notes that there is markedly little knowledge regarding durable conservation efforts [8]. Statements by Firth et al. [7] expressing the clear need for disaggregated data to fully comprehend the consumption patterns of UK households enforces the need for the work presented herein. In addition, Firth et al. [7] considered only one method for grouping appliances into consumptive categories without considering that there may be alternative groupings which may better explain the observed data. This further justifies the current work to assess the appliance consumption patterns which lead to load-shifting and conservation results based on different appliance grouping methods. The new grouping methods used are described as discretionary grouping and major/minor grouping.

2.2.1. Discretionary grouping

The third grouping method, and the first novel approach, is by discretionary/non-discretionary status and is proposed in this work. Discretionary and non-discretionary loads have not been well defined or studied in the literature, but represent a dichotomy between appliances with which the householder actively engages and those with which he/she does not. Discretionary loads in this case include any uses with which a householder must engage in order to stimulate the electrical load. Examples of this would be lighting, media centres, space heating/cooling and laundry. Non-discretionary loads are defined here as those that operate automatically or are necessary for maintaining the house or its occupants and include such items as refrigeration, cooking, sump pumps and water conditioning.

2.2.2. Major/minor grouping

The fourth grouping procedure is also proposed in this work and is unique to each household based on data from the household. This method focuses on finding the uses that contribute much of the household consumption to ascertain whether these major

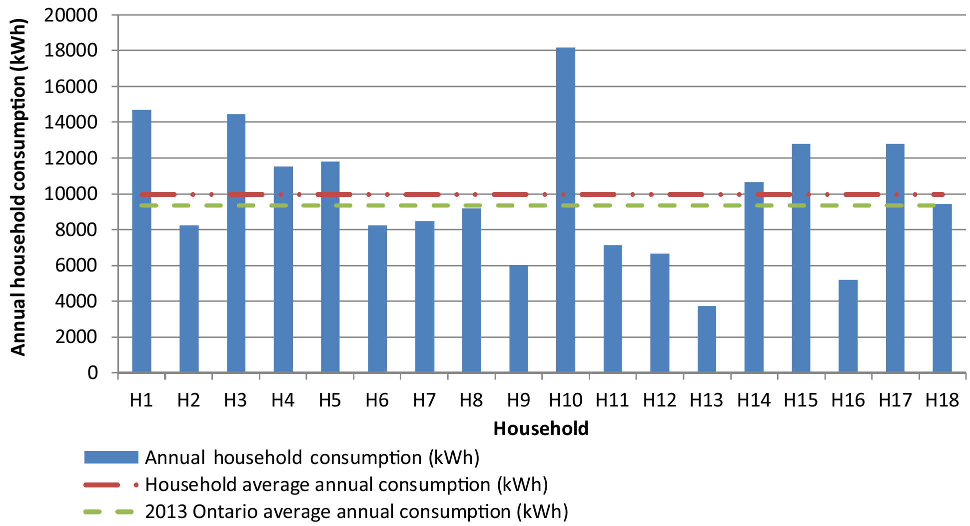

Fig. 1. Annual household consumption for the 18 households considered in this study plotted with the annual average consumption of this group as well as the Ontario average.

uses or the other (minor) uses are contributing more to the overall consumption pattern of the household. For each household, appliances are assessed individually using the disaggregated data and analyzed by month. The top five consumptive appliances are identified for each month and those appearing in the top five for more than 90% of the months studied are selected to be the major consumers. Each household in this study had a different number of circuits monitored, according to the electrical setup in each particular case. As such, some households with a high number of circuits had more end-uses monitored and thus individual circuits might not reach the threshold of being in the top five consumers for more than 90% of monitoring months. Households with a high number of individual circuits had major and minor appliances assessed only by the total usage of the appliances over the course of the monitoring period. Air conditioning in each household, being seasonal in nature, was included as a major appliance for all households as it is typically a major load in the North American context, but may not be identified as such by the above methods.

2.3. *Case study in Ontario, Canada*

Twenty-five households in Milton, Ontario volunteered to be part of the Energy Hub Management System (EHMS) project. Aggregate consumption data for the study households were supplied by the regional utility company, Milton Hydro, as part of the pilot project. In addition, equipment was installed in these households allowing remote monitoring of electrical consumption for each circuit, resulting in a very large disaggregated data set.

Five households withdrew from the program early and thus their data are not considered in the further analysis as data access was limited and further examination of the disaggregated data was not possible. Data collection issues for two households also prevented the data from being used; thus, the original 25 households were reduced to 18 for further consideration in this work. Through aggregate monitoring, it was observed that these 18 households show similar aggregate consumption to the provincial average, as shown in Fig. 1. Further information on the project and time-of-use pricing can be found in our previous work [23]. This builds upon a key area mentioned by Rowlands et al. [24], specifically addressing the area of householder involvement given consumption information. Additionally, this study provides information for system operators in addition to generating comprehensive electricity use data from residential households [24].

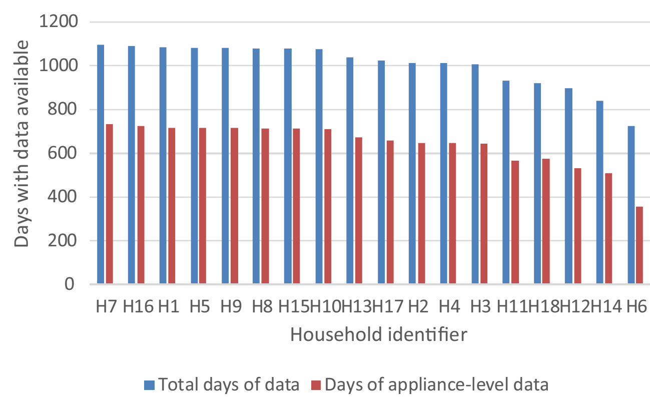

Fig. 2. Data days of the 18 studied households for the first two monitoring years: total number of monitoring days shown in blue (includes baseline year household consumption) and disaggregated monitoring days in red. (The colours referenced in the text only appear in web version of the article.)

The annual average consumption of the households is compared with the average in the province of Ontario, Canada [2] as well as the average of the 18 households in Fig. 1. The households were renumbered from their original designations to express the list as a continuous set and also to further anonymize the households. Additionally, some of the remaining households had later installation dates and thus could only be considered for a portion of the monitoring period as explained in Section 4.3.

Appliance consumption within a household was monitored using two distinct types of equipment directly linked to the household master circuits and was recorded every five minutes. The number of days of data for each of the 18 monitored households for the first two monitoring years are shown in Fig. 2 (this includes one year of base data from the utility partner prior to the installation of in-home hardware). The larger number of days (blue) corresponds to the inclusion of the base year for which the entire household consumption was measured whereas the shorter (red) shows the days for which disaggregated electricity consumption was obtained.

3. Household selection and monitoring systems

The project team selected participants from those who had expressed interest in taking part in new programs, ensuring both high prospects for participant engagement and some level of diversity. Consequently, the selection strategy can be considered to be 'selective sampling'. Across the 18 homes used for this study, equipment was installed that allowed homeowners to monitor and to control key electricity loads. They could access this information – and control these end-uses – by means of a project-specific, secure web portal. Each home was provided with a micro Hub controller (a single board computer), a dedicated router, a wireless thermostat and a web-based Energy Hub Management System account that allowed monitoring and control of electrical consumption for selected appliances in a household. Due to confidentiality reasons of the project partner who installed the equipment, detailed information on the exact equipment and protocols used cannot be disclosed. The systems are described here in as much detail as possible for readers to understand the setup but not the specific technologies.

There were, more specifically, two options:

1. Twelve homes had their original electrical panel replaced with a smart electrical panel, which allowed for detailed monitoring and control across 24 circuits. The installation took between two and three hours, and the owner would also receive two plug-load monitors, in order to measure key individual loads that were grouped together on a circuit. A schematic of this setup is shown in Fig. 3 which shows the equipment and communication between the different hardware involved in the setup.
2. The other six homes kept their original electrical panel but had a multi-channel energy consumption monitor (current transformer) attached to it. This device allowed the measurement of seven circuits from the panel. An additional five plug-load monitors were provided to these houses. A schematic representation of this setup is shown in Fig. 4 and is similar to the previous setup with the notable differences of the Brultech metering device, Zigbee load controller and that the existing electrical panel was used.

Two different monitoring systems were employed in this project to explore the two systems considered to be the 'state of the art' while also considering the price of the different systems, ease of installation and connection with the web portal that was used for controlling them. This was intended to ensure that the approach to household demand monitoring and response could be achieved with more than one hardware setup. The level of aggregation differs slightly between the two setups and thus the additional plug-load monitors in the second setup were intended to compensate for this. While the level of aggregation is thus slightly different between the two setups, it was observed that the number of loads registering consumption was similar for all households, regardless of the hardware installed. Furthermore, the load grouping methods proposed in this work mitigate the difference stemming from aggregation at the hardware level.

Changes in the household makeup such as the number or age of inhabitants was assumed to be stable throughout the study period. At the beginning of the study, no changes in the household sizes were expected and an increasing age of the inhabitants was not considered in the analysis. Unexpected events could have occurred to change the number of inhabitants but this has not been accounted for in this study.

The 18 households considered in this study yielded electrical consumption measurements from 13–25 household circuits every five minutes with monitoring equipment installation taking place in 2011 and 2012 and continuing through February 2014. The total number of appliances monitored was 393 and the dataset in the study period consisted of approximately 74.4 million data points though further aggregation was completed to an hourly basis to ease the analysis. For brevity, the exhaustive list of appliances measured is not presented here, though the relevant loads are shown in Section 5.1 after selecting a subset of the households for deeper analysis.

4. Methodology

The procedure followed in this research and the methods used are described in more detail in this section. Firstly, the households were selected and monitoring equipment installed as discussed in Section 3. Baseline data were collected from the utility provider (one year prior to hardware installation) and appliance-level data were collected from the homes over a period of two years. After the monitoring period, the data are checked for quality and periods of missing data are filled according to the household consumption near the gap in data and weather normalization is considered. The aggregate household data are used to classify the households which have conserved electricity or shifted their consumption to off-peak periods (between 19:00 and 7:00 h during the week in addition to weekends and holidays). The shifting and conserving behavior of the classified households is then scrutinized at the appliance level to find a correlation between the observed shifting/conservation and the consumption of appliance groups by calculating correlation coefficients.

4.1. Data gap filling

Monitoring period length for households varied from 1 to 3 years, during which time there were 'gaps' in the data which could be caused by power outages, user interventions, equipment failures, miscommunication between the hub equipment and the server or for other reasons. Consistent supply of data is integral for quantifying potential reductions in consumption at the household level and therefore it was necessary to develop an algorithm for filling the gaps. These gaps were filled according to the consumption behavior in the same hour for days surrounding each gap, assuming that consumption of appliances would follow a daily routine. Abreu et al. [25] identified patterns in days with similar baseline conditions; accordingly, a similar methodology was devised for this application and it was thus assumed that temporally-similar days are most likely to have a similar consumption pattern. The procedure included the assessment of the number of weekend/holiday (W/H) days and non-holiday weekdays (NHW) contained within the gap period and also in the data before and after the gap. The consumption of each hub-appliance before and after a data gap is analyzed by finding the mean and standard deviation for the 10 days prior to and 10 days after the data gap. Congruency between the two time periods results in the gap being filled by the mean profile from the pre- and post-gap periods for each day as appropriate for its status as a NHW or W/H. In the case that consumption values before and after the gap are not congruent, the pre- and post-gap date range is modified to 14, 21 and 28 days and the same procedure is applied. Failing to have congruent data before and after the gap for any of these periods leads to filling the gap using the most temporally-appropriate data, namely that from the 10 days before and after the data gap. For this algorithm, congruence is defined as means that are within 10% of each other or that are within 50% of the smaller standard deviation from the two periods before and after the gap for more than 50% of the profile in the pre- and post-gap assessment for both NHW and W/H. A flow diagram of the procedure is presented as Fig. 5.

Several consecutive gaps with short intervening periods of good data cannot be treated by the above algorithm. For these cases, the gap is filled by the mean profile from the closest 10-day period of good data. Additionally, gaps longer than 28 days in duration are not filled as they are significant in duration and may also lead to inaccuracy due to seasonal shifts. The data were aggregated to an hourly

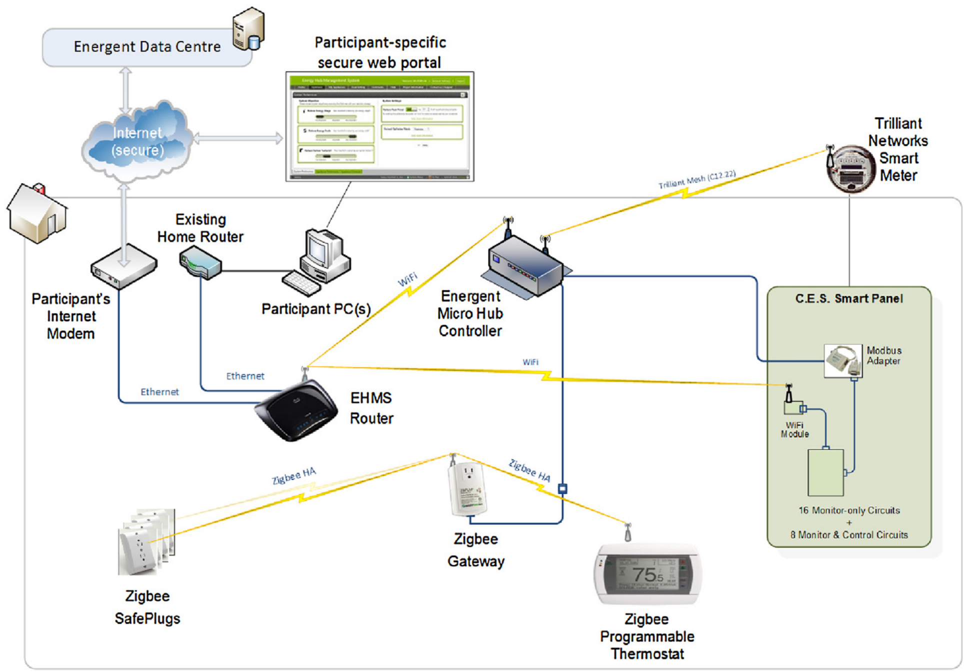

Fig. 3. System schematic for households with a smart panel replacing the existing panel.

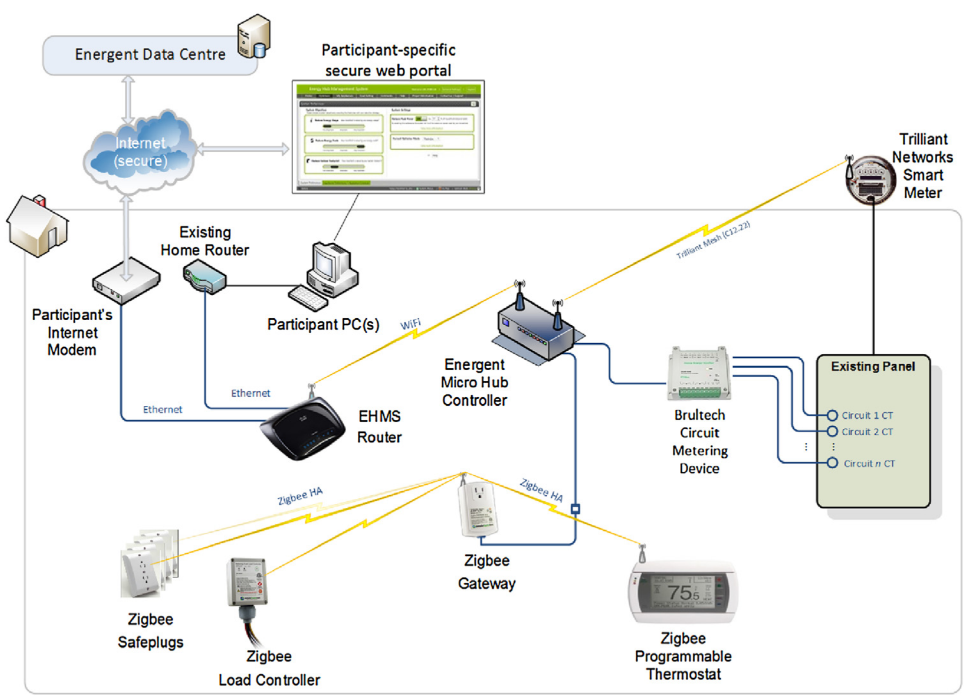

Fig. 4. System schematic for the alternative setup in which the existing electrical panel remains and an intermediate metering device is used.

basis (reducing the number of data points from 74.4 million to 6.5 million) and then filled by this algorithm. A post-procedure assessment of the data gap filling showed that 325 000 data points (5% of the dataset's 6.5 million hourly consumption values) had been filled by the procedure and that 730 (<0.02%) remained unfilled as null values. The number of unfilled values was reported in the subsequent analyses. Periods with greater than 1% of the values as unfilled gaps (null values) were removed from the analysis. A comparison of 16 000 filled data points with an external database showed an average deviation of −0.028 kWh on an average value of 1.13 kWh for an average deviation of 2.5% for the filled data.

4.2. Weather normalization

In the North American context, normalizing electricity consumption based on weather is common practice as the climate in a given area is related to the consumption of electricity. Variations in air temperature for the region studied here are recorded as low as −28 °C and as high as 39 °C between 1981 and 2010 [26], thus conditioning the indoor temperature can have a large impact on electricity use. Typically, monthly electrical usage is correlated with temperature and then predicted for additional days based on the weather patterns. This method is often used as household aggregate

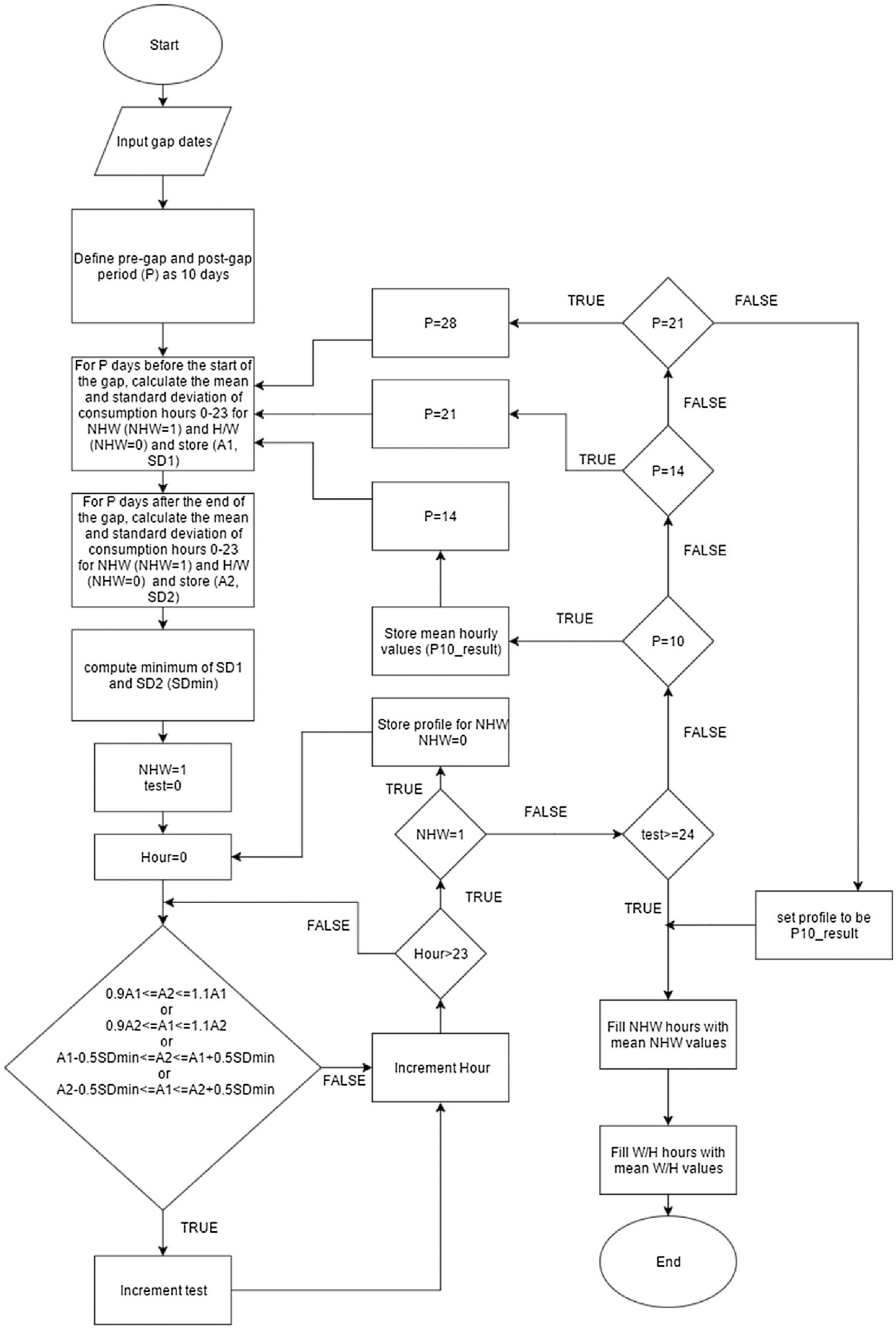

Fig. 5. Flow diagram for gap filling.

electrical consumption is available from householder's electricity bills, whereas the disaggregated data examined in this study yielded direct access to the specific uses within each household and thus it is not required. Furthermore, weather normalization methodology based on E-tracker software developed by Kisock [27,28] was applied to several households but resulted in a very similar electrical consumption pattern for the monitoring years as is actually observed. Since the weather normalization yields only marginal differences in the consumption compared to the observed values, it is concluded to be unnecessary for this study.

4.3. Household classification

A traditional Cartesian approach for displaying performance based on two axes of different indicators was used as a basis for classifying households. In this case, the two metrics of interest were absolute conservation and the percentage of electricity consumed during the off-peak periods. This approach was modified, however, to have nine sectors instead of four quadrants as unintentional modifications or incidental occurrences may cause a slight shift and result in reclassification (e.g., conserver becomes non-conserver or vice-versa) from one quadrant to another for

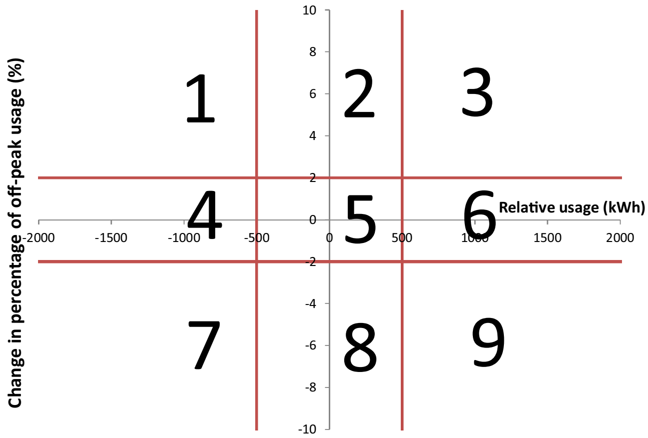

Fig. 6. Sector approach to defining conservation and shifting electricity consumption by households with the x-axis locating households based on absolute conservation and the y-axis expressing a change in the percentage of off-peak consumption.

households close to the origin of either axis. Instead, thresholds for defining households that increased or decreased total consumption and/or the proportion of electricity used off-peak were set at 500 kWh per year for total consumption and 2% for load-shifting. These thresholds are imposed to eliminate incidental modifications from impacting the results of the classification and are based on reasoning that such a change would likely not be reached without effort on the part of the householder. Thus, instead of the traditional four quadrants to describe a household's consumption characteristics, nine sectors are used. These sectors serve to separate notable changes relative to the comparison period from the others and buffer each axis to encompass changes in consumption that may be attributable to unintended alterations in electricity use. The nine sectors are identified as shown in Fig. 6 and separate households that have conserved, shifted consumption to off-peak or exhibit opposite behavior or no change in these areas. The metrics chosen to represent these impacts are the relative change in absolute consumption (on the x-axis) and the change in percentage of off-peak consumption (on the y-axis). These choices reflect what are considered to be important for both the utility and the consumer. Reducing the absolute consumption reflects the desire of utilities to avoid constructing new generation and also would reduce the overall electricity bill for the householder. Shifting electricity demand to off-peak times benefits the generators by avoiding construction of new peaking generation and benefits the householder by providing electricity at a lower cost. For determining the x-coordinate, Eq. (1) is used to calculate the relative absolute consumption between the monitoring period and the base year. The superscripted + in the following equations denotes the import of electricity from the grid and is utilized to make the equations generic in case an electricity export would be considered in future work (which would appear as E^-).

$$\Delta E_h^+ = \sum_{t=1}^{n_{t,y}} E_{t,y,h}^+ - \sum_{t=1}^{n_{t,0}} E_{t,0,h}^+ \tag{1}$$

Where $E_{t,y,h}^+$ is the electricity usage in time-step t of year y for household h, $n_{t,y}$ is the number of time-steps in year y and thus ΔE_h^+ is the change in electricity consumption between year y and the base year (0) for household h. The y-coordinate for the plot is calculated by a similar method, expressed as a difference of off-peak electrical consumption relative to the total consumption between year y and the base year as shown in Eq. (2).

$$\Delta E_h^{off} = \left[\frac{\sum_{t=1}^{n_{t,y}} E_{t,y,h}^{off}}{\sum_{t=1}^{n_{t,y}} E_{t,y,h}^{+}} - \frac{\sum_{t=1}^{n_{t,0}} E_{t,0,h}^{off}}{\sum_{t=1}^{n_{t,0}} E_{t,0,h}^{+}} \right] \cdot 100 \tag{2}$$

Where $E_{t,y,h}^{off}$ is the consumption of off-peak electricity at time t in year y and thus ΔE_h^{off} is the change in the off-peak consumption between year y and the base year (0) for household h. The calendar dates of the base year were always 365 days before the installation date of the in-home monitoring equipment but varied based on each household. Seasonal variation and other variables were eliminated in this way, as an entire year was considered for the base data. The time step considered in this study to classify the households was hourly, in accordance with the data received from the utility provider for the base year.

4.4. Pearson correlation coefficient

Pearson correlation coefficients are a measure of the linear relationship between two measured quantities [29]. For this study, the Pearson correlation coefficient is selected as the key method for analyzing the relation between consumption in an appliance group and overall household consumption. Other statistical methods exist, but the Pearson relation is the most logical choice for this application as a linear relation is expected between appliance group usage and overall household usage. For example, a 1 kWh reduction in appliance use is expected to show a 1 kWh conservation in the overall household consumption. Thus, the Pearson correlation coefficient is a measure of whether household electricity conservation is directly attributable to an appliance group. One weakness of this method is that it does not capture non-linear, monotonic correlations – that is – non-linear relations between the dependent and independent variables, though values could both be changing in the same direction, e.g., exponential or power-law relations. Since this analysis is intended to ascertain the direct impact of appliance group consumption on the overall household consumption, the relations are expected to be linear. The equation for calculating the correlation coefficient is expressed as shown in Eq. (3) [29].

$$r = \frac{\Sigma(X - \overline{X})(Y - \overline{Y})}{\sqrt{(\Sigma(X - \overline{X})^2)}\sqrt{(\Sigma(Y - \overline{Y})^2)}} \tag{3}$$

In this study, the correlation coefficient is calculated between the change in overall household consumption or load shifting and the change in consumption at the appliance level to assess whether the change in household consumption can be attributed to specific appliance groups. Thus, X in Eq. (3) is the appliance-group consumption for time t in year y and Y is the change in household consumption calculated by Eq. (4) for time t and year y relative to the same period in the previous year (y-1) or the change in off-peak consumption percentage in time t compared to the same period in the previous year (y-1) as shown in Eq. (5). For this study, the periods compared using this method were the monthly aggregates of the appliance group consumptions to smooth the high variability from shorter periods.

$$\Delta E_{t,y,h}^+ = E_{t,y,h}^+ - E_{t,y-1,h}^+ \tag{4}$$

$$\Delta E_{t,y,h}^{off} = \left[\frac{E_{t,y,h}^{off}}{E_{t,y,h}^{+}} - \frac{E_{t,y-1,h}^{off}}{E_{t,y-1,h}^{+}} \right] \cdot 100 \tag{5}$$

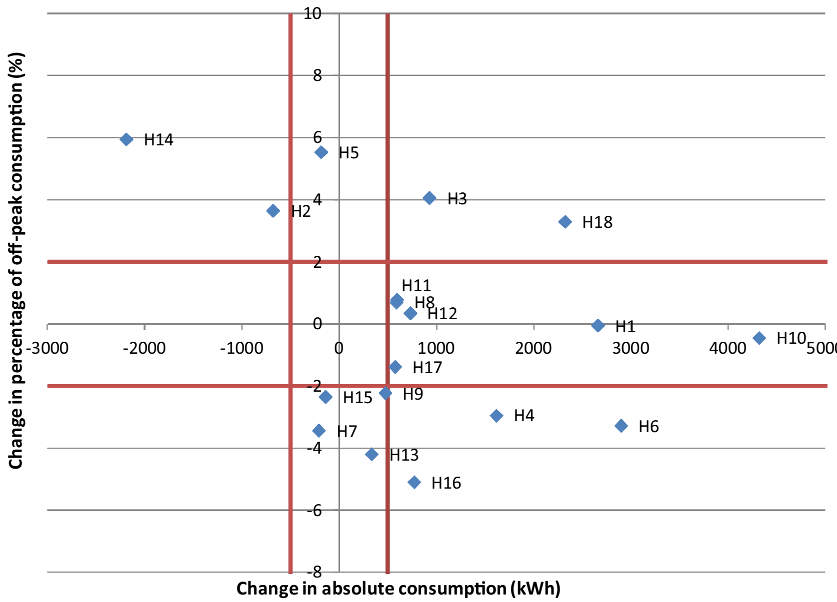

Fig. 7. Change in proportion of off-peak consumption and total consumption of the second monitoring year relative to the base year (H13-H18 consider 9 relative months accounting for later equipment installation dates).

Table 1
Annual average electrical consumption for the 18 households included in the analysis.

Household	Annual Average consumption (kWh)
H1	14700
H2	8200
H3	14400
H4	11600
H5	11800
H6	8200
H7	8500
H8	9200
H9	6000
H10	18200
H11	7100
H12	6700
H13	3700
H14	10700
H15	12800
H16	5200
H17	12800
H18	9400

5. Results

The first step in the assessment was to identify the households that had shifted or reduced consumption. The installation of monitoring equipment in homes can enable householders to make better-informed decisions regarding electricity consumption and be measured through time relative to the baseline year prior to installation of the equipment. As the aim of this study was to identify the households which had shown changes that persisted after the initial monitoring period, data from the second monitoring year were used to classify them according to their change in consumption and change in percentage of off-peak consumption. The resultant changes in proportion of off-peak consumption and total consumption for the 18 households are plotted on the 9-sector grid described in Section 4.3 and shown in Fig. 7. These results are relative to the baseline data and thus the results reflect the differences of household usage and off-peak consumption percentage relative to the baseline consumption. The average annual consumption of each household is shown in Table 1 to provide additional context for Fig. 7.

The location of households within the three sectors at the top portion of the figure showed that these households had increased their share of consumption during off-peak periods. These households are labelled H2, H3, H5, H14 and H18. The other notable group lies in the left-most sectors (1, 4 and 7) where overall consumption within the household declined relative to the baseline year (H2 and H14). As such, the result for monitoring year 2 compared to the baseline year was that five households had shifted their consumption to be increasingly off-peak, while two had reduced their total consumption. The two groups of 'shifting households' and 'conserving households' are the focus of subsequent analysis to understand what appliance groups were responsible for these changes. These households have shown success in shifting the timing of electricity use, the overall level of consumption or both and are considered to be the model case for other households. The further analysis in this work was focused on determining the appliance groups that showed consumption patterns reflected by the overall trend to determine a potential focus for other households to find success. It is important to note for the analysis conducted here that H2, H3 and H5 had 24–25 monitored circuits while H14 and H18 had 13 and 15 monitored circuits, respectively. This difference was due to different technology installed at these houses but this did not present a problem for the grouping methods used in this study as it was still apparent which group each consumption belonged to.

5.1. Appliances monitored for the households identified

The households identified above are each unique in the number of monitored circuits as well as differing circuit aggregation. A table of the monitored circuits is shown in Table 2.

The contribution of the consumption for the unknown or non-descript circuits was considered with respect to the total household consumption. Cases in which the consumption contributed more than 1% of the total for a household were investigated to obtain further clarity on the loads associated with each circuit.

5.2. Shifters

Pearson correlation coefficients were calculated for each appliance in the shifting households to assess the strength of the relation

Table 2
Appliance list for conserving and shifting households.

H2	H3	H5	H14	H18
Air conditioner	Air conditioner	Air conditioner	Air conditioner	Air conditioner
Basement	Basement outlet	Bedroom outlet 1	Clothes dryer	Clothes dryer
Basement bathroom	Bedroom 1	Bedroom outlet 2	Clothes washer	Clothes washer
Bedroom 1	Bedroom 2	Central vac	Dishwasher	Dishwasher
Bedroom 2	Clothes dryer	Clothes dryer	Furnace	Furnace
Bedroom 3 and extra freezer	Clothes washer	Clothes washer	Home office 1	Home office 1
Bedroom 4	Dining room outlets	Dishwasher	Home office 2	Home office 2
Clothes dryer	Dishwasher	Furnace	Home office 3	Kitchen microwave
Computer	Exterior outlet	Garage	Home office 4	Kitchen toaster
Electric heater	Furnace	Gas water heater blower	Media centre 1	Media centre 1
Front hall outlets	Garage	Kitchen plugs 1	Media centre 2	Media centre 2
Furnace	Kitchen 1	Kitchen plugs 2	Oven	Media centre 3
Garage	Kitchen 2	Kitchen plugs 3	Refrigerator	Media centre 4
Kitchen subpanel	Media centre	Main washroom	Smart meter	Refrigerator
Laundry room and outdoor outlets	Media centre 2	Media centre 1		Smart meter
Smart meter	Office equipment	Media centre 2		Stove
Smart panel	Refrigerator	Media centre 3		
Unspecified outlets 1	Plug #2 upper	Media centre 4		
Unspecified outlets 2	Smart meter	Panel plug		
Water filter	Smart panel	Pot lights		
Wireless router	Stove	Refrigerator		
	Sump pump	Smart meter		
	Unknown 1	Smart panel		
	Unknown 2	Stove		
	Unknown 3	Sump pump		
	Unknown 4	Unknown		
		Unknown 2		

Table 3
Positively correlated off-peak circuit consumption with household off-peak usage for shifting households.

Household	Circuit					
H2	Clothes dryer	Bedroom 3 and extra freezer	Bedroom 1	Unspecified outlets 1	Garage	
H3	Clothes dryer	Basement outlet	Dishwasher	Refrigerator		
H5	Main washroom	Bedroom outlet 2	Dishwasher	Furnace	Garage	Gas water heater and blower
H14	Clothes washer	Dishwasher				
H18	Media centre					

between the appliance and the overall household consumption patterns relative to the base year. For brevity, only appliances showing a correlation are presented here. Tables 3 and 4 show the relevant individual circuits, defined as having a Pearson correlation coefficient with the household consumption data relative to the base year of at least 0.4 which indicated at least a moderate correlation.

Table 3 shows that individual circuit consumption for some individual uses were correlated with the overall household consumption pattern. These positive correlations show that fluctuations in the individual circuit consumption directly contribute to the overall household pattern. Common appliances across several households are observed such as bedroom plugs, garage plugs, dishwashers and laundry appliances. These disaggregated, circuit level results show that changing the time of use for several common appliances can have a noticeable impact on the overall ToU pattern in a household. The negative correlations are shown in Table 4 and represent those appliances that have changed in the opposite direction and therefore hinder efforts to shift consumption to off-peak periods.

Table 4
Negatively correlated off-peak circuit consumption with household off-peak usage for shifting households, H3 and H5 omitted due to an absence of negatively correlated off-peak circuits.

Household	Circuit	
H2	Air conditioner	Bedroom outlet
H14	Office outlet (router, printer)	
H18	Office outlet (computer equipment)	

Table 4 shows fewer uses having a negative correlation with overall household consumption but the notable uses were office plugs, an air conditioner and bedroom plugs. This provided further evidence that these circuits had the ability to impact the overall household ToU pattern in a noticeable way. It is interesting that H2 has bedroom circuits with positive and negative correlations. The implication may be that different members of the household made different decisions about when to use their electrical devices.

The same analysis was also conducted for the groups of appliances identified earlier in Sections 2.1 and 2.2 to examine the correlation between appliance group consumption and the overall pattern relative to the base year. The appliance groupings shown in Table 5 consist of the electricity uses identified by the DECADE program in the United Kingdom plus the additional group of space conditioning that is more applicable in the North American context as described in Section 2.1.1. The results of this analysis, comparing group off-peak share of consumption with household off-peak share relative to the base year, are shown in Table 5 with correlation coefficients 0.40–0.59 highlighted in orange and 0.60–0.79 in green.

This assessment showed a moderate correlation between uses in the brown and wet appliance areas and the overall household consumption patterns. H2 showed moderate correlations between overall household consumption and that exhibited by the refrigeration and wet appliances and a strong correlation with the brown appliances. H3 showed moderate correlations with brown and wet appliances while H5 showed a moderate correlation with brown, wet and space conditioning uses and H14 with only the wet appli-

Table 5
Correlation coefficients of appliance groups with off-peak share relative to the base year by DECADE group.

	Lighting	Refrigeration	Brown	Wet	Cooking	Space Conditioning
H2	−0.051	0.459	0.730	0.492	0.203	0.395
H3	0.000	0.370	0.524	0.530	0.297	0.127
H5	0.307	0.285	0.540	0.478	0.346	0.461
H14	N/A	0.013	0.379	0.434	0.302	−0.043
H18	N/A	−0.115	−0.307	0.275	0.012	−0.199

Table 6
Correlation coefficients of appliance groups with off-peak share relative to the base year by user interaction group.

	Continuous	Standby	Cold	Active
H2	N/A	0.352	0.459	0.789
H3	0.354	0.000	0.423	0.597
H5	0.57	0.175	0.285	0.597
H14	N/A	0.379	0.013	0.443
H18	N/A	−0.307	−0.115	0.275

Table 7
Correlation coefficients of appliance groups with off-peak share relative to the base year by discretionary group.

	Discretionary	Non-discretionary
H2	0.486	0.266
H3	0.582	0.515
H5	0.627	0.470
H14	0.271	0.013
H18	0.015	−0.057

ances. H18 did not show notable correlations between any group and the off-peak share of usage relative to the base year.

Utilizing a user interaction grouping system similar to that employed by Firth et al. [7] yielded the correlation coefficients shown in Table 6. This method of grouping differentiates between continuous, standby, cold and active uses. The circuit descriptions did not identify many instances of continuous use such as alarm clocks and smoke detectors as these were not specified on the circuit diagrams for the study households. These loads are typically small and likely not subject to change within a household; as such, the impact on household proportion of off-peak consumption is assumed to be negligible for households without distinct references to continuous uses. The exception is within H5 where a sump pump, smoke alarm and natural gas water heater showed a moderate correlation with the overall household consumption relative to the base year. Standby appliances did not show notable correlations between off-peak consumption and the household pattern relative to the baseline year for any of the five shifting households. Cold appliances showed a moderate correlation with the overall household pattern in H2 and H5 while active appliances exhibited a moderate to high correlation in every household except H18. Though this assessment was aimed at load-shifting correlations, it did correspond to a smaller increase in consumption for active appliances than the overall pattern as shown by Firth et al. [7]. This result suggests that householders may be more able or willing to reduce consumption from active appliances without managing the continuous, standby and cold appliances with the same vigilance.

The third grouping system assigned loads to either the discretionary or non-discretionary categories. For this grouping, the results of the analysis are shown by correlation coefficients in Table 7. These results showed that H2, H3 and H5 exhibited moderate to strong correlations with the discretionary loads. H3 and H5 also showed moderate correlations with non-discretionary loads though with slightly smaller correlation coefficients. H14 and H18 did not have notable correlations using this grouping method.

Table 8
Correlation coefficients of appliance groups with off-peak share relative to the base year for the major/minor grouping method.

	Major	Minor
H2	0.787	0.633
H3	0.489	0.655
H5	0.581	0.284
H14	0.220	0.353
H18	−0.156	0.218

Appliances grouped into major and minor loads for each household according to the procedure outlined in Section 2.2.2 yielded the correlation coefficients in Table 8. Separating electrical uses into major and minor loads showed a strong or moderate correlation for H2, H3 and H5 with the correlation coefficient for H2 bordering on very strong. Additionally, H2 and H3 showed strong correlations with minor appliances. H2 and H3 had the highest number of appliances and thus a higher level of disaggregation in measurements. This led to consumption spread across more circuits, thus making the segregation between major and minor appliances less dichotomous. As with the discretionary grouping, correlation coefficients showed little correlation with major or minor uses in H14 and H18.

It is clear from Tables 3 and 4 that individual appliances can have notable impacts on the overall off-peak consumption patterns for households. The subsequent Tables 5–8 further assessed the correlations between overall household consumption patterns and the usage of appliances grouped by several methods. Brown and wet appliance groups showed moderate correlations for three and four households, respectively. Active appliances in the grouping method described by Firth et al. [7] also showed moderate correlations with the overall household consumption pattern relative to the baseline year. Discretionary and major/minor grouping methods showed moderate to strong correlations in three households but no distinct correlations in H14 or H18. H2 had a strong correlation between brown and active appliances and the proportion of off-peak consumption relative to the base year. Other strong correlations were observed for discretionary appliances in H5, major and minor appliances in H2 and minor appliances in H3. A summary of each grouping category with the correlation coefficient displayed for each household is shown in Fig. 8.

5.3. Conservers

The two households identified in Section 5 as being conservers throughout the monitoring period are H2 and H14. Similar analysis to the off-peak assessments was completed for these households based on appliance consumption. Individual circuits were assessed for correlations with the overall household consumption relative to the base year and the positive correlations are shown in Table 9.

Table 9
Positively correlated circuit consumption with relative household usage for conserving households.

Household	Circuit
H2	Air conditioner
H14	Air conditioner

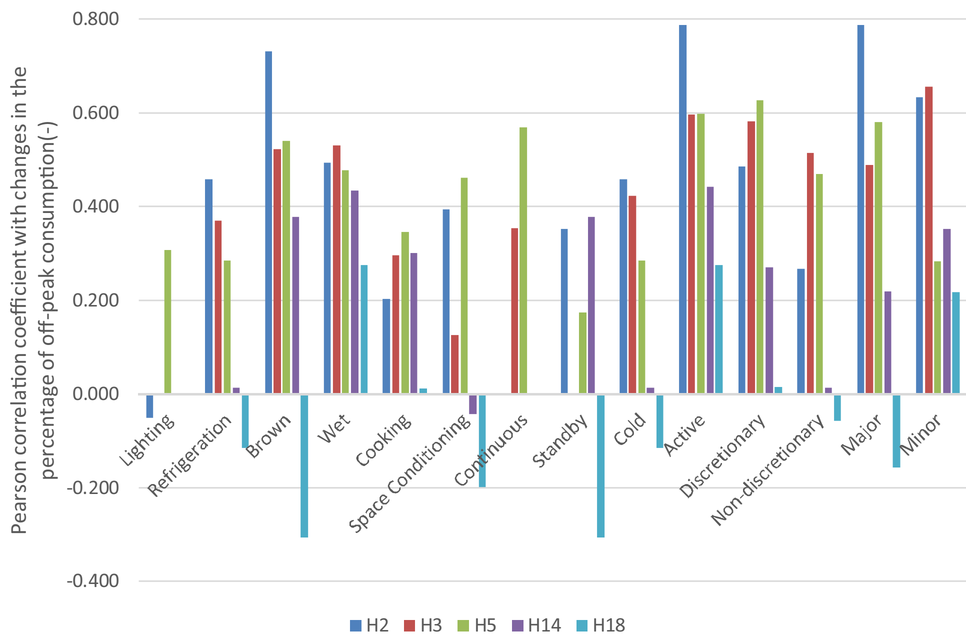

Fig. 8. Summary chart of Pearson correlation coefficients for appliance group consumption shifting with household consumption shifting. Higher values denote higher correlations and negative values represent reverse correlation.

Table 9 clearly indicates that overall household electrical conservation is positively correlated with the consumption of the air conditioning unit. The households showing conservation results represented only 10% of those monitored, but a reduction in the consumption of the air conditioner was clearly identified in both conserving households as being correlated to the overall pattern.

Table 10 shows the circuits with moderate negative correlation coefficients with the overall household consumption for the conserving households. Only three circuits were identified: a kitchen circuit, an office circuit and a combined circuit from laundry, fireplace and outdoor outlets. These negative correlations indicated that the above uses changed in the opposite direction to the overall conservation pattern. It should be noted that the analysis was not able to indicate whether the consumption of these appliances had increased (thus offsetting other conservation efforts) because disaggregated data were not available prior to the installation of the equipment.

The first group assessment again utilized the DECADE program groupings and the correlation coefficients are shown in Table 11. The space conditioning category, added for this study as mentioned in Section 2.1.1, is the only category that had a moderate correlation with household consumption pattern relative to the base year. This finding contrasts with the results presented in Table 5 for off-peak shifting but further reinforces the need to address air conditioning electrical consumption in North America. Considering that the individual air conditioning appliances for both conserving households were correlated with household conservation patterns as shown in Table 9, this result from Table 11 was expected. The remaining categories did not show notable correlations with the overall household consumption relative to the base year.

Table 10
Negatively correlated circuit consumption with relative household usage for conserving households.

Household	Circuit	
H2	Kitchen outlet (not cooktop)	Laundry room and outdoor outlets
H14	Office outlet (router, printer)	

Table 12
Correlation coefficients of appliance groups with household consumption relative to the base year by user interaction group.

	Continuous	Standby	Cold	Active
H2	N/A	−0.170	−0.228	0.056
H14	N/A	0.246	0.311	0.264

The data were similarly assessed by the second grouping method (interaction grouping) in Table 12. Grouping appliances based on the householder interaction with the appliance did not show any meaningful correlation with the profile of household electricity consumption relative to the base year. The electrical conservation observed in these households does not appear to fit the appliance grouping method utilized by Firth et al. [7], though the geography and climate likely play a significant role. Table 13 shows the correlation coefficients from the discretionary grouping for the conserving households.

Both of the conserving households, H2 and H14, shown in Table 13 demonstrated conservation in discretionary loads which reflected the overall conserving trend in the households. For the load-shifting assessment, households showed correlations with both discretionary and non-discretionary loads but for conservation, the correlations were apparent for discretionary loads but not for non-discretionary loads. The analysis for major and minor loads, the last grouping of uses, is shown in Table 14.

As with the discretionary grouping from Table 13, there were clear correlations between major uses of electricity in the conserv-

Table 11
Correlation coefficients of appliance groups with household consumption relative to the base year by DECADE group.

	Lighting	Refrigeration	Brown	Wet	Cooking	Space Conditioning
H2	0.322	−0.228	−0.102	−0.272	−0.273	0.531
H14	N/A	0.311	0.246	0.267	0.020	0.531

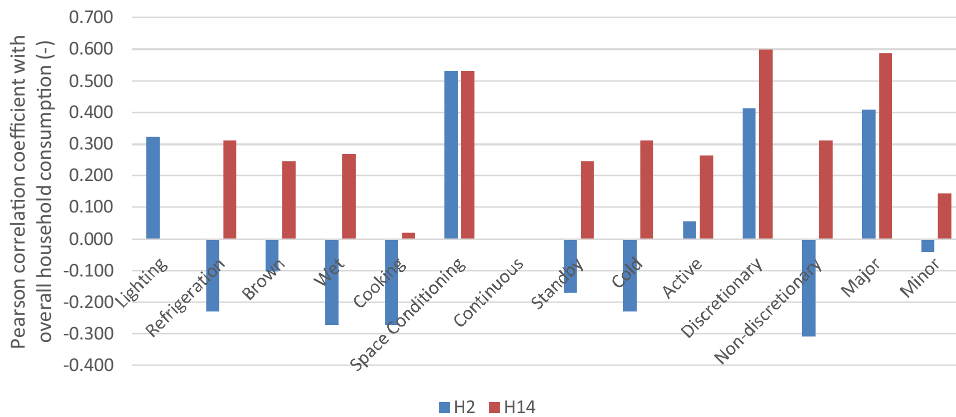

Fig. 9. Summary chart of Pearson correlation coefficients for appliance group consumption with changes in household consumption. Higher values denote higher correlations and negative values represent reverse correlation.

Table 13
Correlation coefficients of appliance groups with household consumption relative to the base year by discretionary group.

	Discretionary	Non-discretionary
H2	0.415	−0.309
H14	0.599	0.311

Table 14
Correlation coefficients of appliance groups with household consumption relative to the base year by major/minor group.

	Major	Minor
H2	0.408	−0.042
H14	0.586	0.143

ing households and the household profile of conservation over the monitoring period.

The consensus reached from the two conserving households showed that they have achieved reductions in electrical consumption relative to the base year by altering their usage patterns. It is notable that the air conditioning system had a positive correlation with the household consumption pattern. The specific appliance groupings that had notable correlations with household consumption were space conditioning, major appliances and discretionary appliances. A summary of the two conserving households and the correlation coefficients for each appliance grouping are provided in Fig. 9.

Analysts have explored the role of feedback in reducing consumption of electricity with limited mention of load-shifting from peak to off-peak periods. Results presented here showed that five households of 18 shifted consumption to increasingly off-peak and two conserved electrical use relative to a baseline year. The finding that only two of 18 households conserved relative to a baseline period contrasts with the literature findings that feedback stimulates conservation. Firth et al. [7] found similar mixed results and cited many possibilities for the lack of conservation in households including newly-built homes, expanding families and others.

The disaggregated nature of the data during the monitoring period allowed for correlation coefficients between groups of appliances and the overall household consumption pattern to be calculated. The conserving and shifting households showed differing results for these correlations across four distinct appliance grouping methods. The proportion of off-peak space conditioning consumption, for example, had a moderate correlation with the overall household pattern in a single household whereas both conserving households showed moderate correlations between space conditioning usage and household consumption.

The different grouping methods assessed in this work indicated that groups differed in their correlative strength depending on whether the analysis was focused on shifting demand or absolute conservation. Analysis of demand shifting showed that each grouping method yielded moderate or strong correlations with at least one category though the highest number of correlations were found using the DECADE grouping which was also the method with the highest level of disaggregation. The strongest correlations for load-shifting were found using the major/minor appliance grouping method. For households with an absolute conservation relative to the base year, all grouping methods except the user interaction method showed similar results in that one appliance category was dominant. The highest correlation was found using a split between discretionary and non-discretionary appliances though all three grouping methods yielded similar results but in different categories.

6. Conclusions

The sample size for this study is relatively small and cannot be considered fully representative of the whole population from which the sample was taken. Nevertheless, as shown by the literature on energy management (e.g., Hargreaves et al. [30]), studies with small sample sizes can make valuable contributions in at least two ways. Firstly, they can inform policy and decision-making by catalyzing new areas for discussion and illuminating new system dynamics. Secondly, they can offer lessons for subsequent investigations with larger, and thus more representative, samples.

Household electricity conservation and demand-shifting are decoupled for this study and it was shown that these performance indicators yielded differing results for different appliance grouping scenarios. Electricity demand shifting was most highly correlated with brown and wet appliances (DECADE grouping), active appliances, discretionary appliances and major uses.

Conservation categories are clear for the two households that showed positive conservation results. The space conditioning category from DECADE grouping and the discretionary and major appliances from the two proposed methods (discretionary and major/minor) showed the highest correlations with overall conservation. Individual circuit analysis identified a reduction in air conditioning consumption with overall household conservation.

Depending on the goal of policy, these identified areas for demand-shifting and conservation serve as indicators pointing to where incentive programs might be most impactful as these modifications appear to be the most acceptable for householders. Other households, without monitoring equipment, may realize similar impacts if utilities or policy-makers use targeted campaigns in these areas.

Policy goals of peak-shifting should focus on brown appliances (e.g., media centres, home electronics, computers, outlets for tools and electronics), wet appliances (e.g., dishwashers, laundry machines, water heaters) and active appliances (e.g., dishwashers, laundry machines, stoves, microwaves, lighting). Efforts to stimulate overall conservation of electricity should focus on space conditioning, discretionary loads and major uses differentiated by household.

This analysis showed several methods for categorizing consumption and the consumption patterns associated with household time-of-use shifting and conservation. Future studies will focus on individual appliances and their usage patterns through time to more accurately understand the impact of feedback on individual appliance consumption.

Acknowledgements

This research was completed under the auspices of the Energy Hub Management System project, which is supported by the Ontario Centres of Excellence, Hydro One Networks Incorporated, Milton Hydro Distribution Incorporated and Energent Incorporated, a Rodan Energy Solutions company. Valuable work on related topics by graduate students and other members of the Sustainable Energy Policy group at the University of Waterloo helped to inform thinking in this area. The authors are grateful for this support; they, however, remain solely responsible for the contents of this article.

References

[1] P. Pourbeik, The anatomy of a power grid blackout – Root causes and dynamics of recent major blackouts, IEEE Power Energy Mag. 4 (2006) 22–29.
[2] Ontario Ministry of Energy, Conservation First: A Renewed Vision for Energy Conservation in Ontario, Ontario Ministry of Energy, Toronto, Ontario, 2013, http://www.energy.gov.on.ca/docs/en/conservation-first-en.pdf (Accessed 1 January 2014).
[3] Ontario Ministry of Energy and Infrastructure, Achieving Balance: Ontario's Long-Term Energy Plan, Ontario Ministry of Energy, Toronto, Ontario, 2013 http://www.energy.gov.on.ca/docs/LTEP_2013_English_WEB.pdf.
[4] A. Faruqui, N. Lessem, S. Sergici, D. Mountain, F. Denton, B. Spencer, C. King, Analysis of Ontario's Full Scale Roll-out of TOU Rates – Final Study, Ontario, Canada, 2016, http://www.brattle.com/system/news/pdfs/000/001/061/original/Analysis_of_Ontario%E2%80%99s_Full_Scale_Roll-out_of_TOU_Rates_-_Final_Study.pdf?1463069898 (Accessed 27 June 2016).
[5] W. Abrahamse, L. Steg, C. Vlek, T. Rothengatter, The effect of tailored information, goal setting, and tailored feedback on household energy use, energy-related behaviors, and behavioral antecedents, J. Environ. Psychol. 27 (2007) 265–276, http://dx.doi.org/10.1016/j.jenvp.2007.08.002.
[6] W. Abrahamse, L. Steg, C. Vlek, T. Rothengatter, A review of intervention studies aimed at household energy conservation, J. Environ. Psychol. 25 (2005) 273–291, http://dx.doi.org/10.1016/j.jenvp.2005.08.002.
[7] S. Firth, K. Lomas, A. Wright, R. Wall, Identifying trends in the use of domestic appliances from household electricity consumption measurements, Energy Build. 40 (2008) 926–936, http://dx.doi.org/10.1016/j.enbuild.2007.07.005.
[8] S. Darby, C. Liddell, D. Hills, D. Drabble, Smart Metering Early Learning Project: Synthesis Report, Environmental Change Institute, University of Oxford, University of Ulster, Tavistock Institute, England, 2015, https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/407568/8_Synthesis_FINAL_25feb15.pdf (Accessed March 31, 2015).
[9] A. Faruqui, S. Sergici, A. Sharif, The impact of informational feedback on energy consumption—a survey of the experimental evidence, Energy 35 (2010) 1598–1608, http://dx.doi.org/10.1016/j.energy.2009.07.042.
[10] T. Ueno, F. Sano, O. Saeki, K. Tsuji, Effectiveness of an energy-consumption information system on energy savings in residential houses based on monitored data, Appl. Energy 83 (2006) 166–183, http://dx.doi.org/10.1016/j.apenergy.2005.02.002.
[11] I. Dent, T. Craig, U. Aickelin, T. Rodden, An Approach for Assessing Clustering of Households by Electricity Usage, 2012, http://eprints.nottingham.ac.uk/2033/ (Accessed 17 October 2014).
[12] C. McKerracher, J. Torriti, Energy consumption feedback in perspective: integrating Australian data to meta-analyses on in-home displays, Energy Effic. 6 (2012) 387–405, http://dx.doi.org/10.1007/s12053-012-9169-3.
[13] C. Fischer, Feedback on household electricity consumption: a tool for saving energy? Energy Effic. 1 (2008) 79–104, http://dx.doi.org/10.1007/s12053-008-9009-7.
[14] S. Darby, The Effectiveness of Feedback on Energy Consumption, Environmental Change Institute, University of Oxford, University of Oxford, 2006.
[15] I. Matsukawa, The effects of information on residential demand for electricity, Energy J. 25 (2004) 1–17.
[16] V.G. Ferreira, The analysis of primary metered half-hourly electricity and gas consumption in municipal buildings. (2009). https://www.dora.dmu.ac.uk/xmlui/handle/2086/3268 (Accessed 17 October 2014).
[17] N. Brown, A.J. Wright, New approaches to gathering, analysis and interpretation of half hourly energy metering data from buildings, Int. J. Low-Carbon Technol. 2 (2007) 80–96, http://dx.doi.org/10.1093/ijlct/2.1.80.
[18] P.C. Reiss, M.W. White, Household electricity demand, revisited, Rev. Econ. Stud. 72 (2005) 853–883, http://dx.doi.org/10.1111/0034-6527.00354.
[19] O.I. Asensio, M.A. Delmas, Nonprice incentives and energy conservation, Proc. Natl. Acad. Sci. 112 (2015) E510–E515, http://dx.doi.org/10.1073/pnas.1401880112.
[20] Energy and Environment Programme, Environmental Change Unit, DECADE: First year report, University of Oxford, University of Oxford, 1995 http://www.eci.ox.ac.uk/research/energy/downloads/decade1.pdf.
[21] B. Boardman, D. Favis-Mortlock, M. Hinnells, K. Lane, G. Milne, J. Palmer, E. Small, V. Strang, J. Wade, DECADE: Domestic Equipment and Carbon Dioxide Emissions, University of Oxford, Second Report, Environmental Change Institute, 1995.
[22] CaRB consortium, Carbon Reduction in Buildings (CaRB), (n.d.). http://www.carb.org.uk.
[23] I. Kantor, I.H. Rowlands, P. Parker, B. Lazowski, Economic feasibility of residential electricity storage systems in Ontario, Canada considering two policy scenarios, Energy Build. 86 (2015) 222–232, http://dx.doi.org/10.1016/j.enbuild.2014.10.022.
[24] I.H. Rowlands, T. Reid, P. Parker, Research with disaggregated electricity end-use data in households: review and recommendations, Wiley Interdiscip. Rev. Energy Environ. (2014), http://dx.doi.org/10.1002/wene.151.
[25] J.M. Abreu, F. Câmara Pereira, P. Ferrão, Using pattern recognition to identify habitual behavior in residential electricity consumption, Energy Build. 49 (2012) 479–487, http://dx.doi.org/10.1016/j.enbuild.2012.02.044.
[26] E. Canada, Canadian Climate Normals – Environment Canada, 2013, http://climate.weather.gc.ca/climate_normals/results_1981_2010_e.html?stnID=4937&lang=e&dCode=0&province=ONT&provBut2:07 pm=Go&month1=0&month2=12 (Accessed 16 March 2015).
[27] J. Kelly Kissock, Measuring industrial energy savings, Appl. Energy. 85 (n.d.) 347–361.
[28] J.K. Kissock, T.A. Reddy, D.E. Claridge, Ambient-Temperature regression analysis for estimating retrofit savings in commercial buildings, J. Sol. Energy Eng. 120 (1998) 168–176, http://dx.doi.org/10.1115/1.2888066.
[29] B.M. Ayyub, R.H. McCuen, Probability, Statistics, and Reliability for Engineers and Scientists, third edition, CRC Press, 2012.
[30] T. Hargreaves, M. Nye, J. Burgess, Keeping energy visible? Exploring how householders interact with feedback from smart energy monitors in the longer term, Energy Policy. 52 (2013) 126–134, http://dx.doi.org/10.1016/j.enpol.2012.03.027.