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Adaptation and validation of an existing bottom-up model for simulating temporal and inter-dwelling variations of residential appliance and lighting demands

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The design and analysis of community-scale energy systems and incentives is a non-trivial task. The challenge of such undertakings is the well documented uncertainty of building occupant behaviours. This is especially true in the residential sector, where occupants are given more freedom of activity compared to work environments. Further complicating matters is the dearth of available measured data. Building performance simulation tools are one approach to community energy analysis, however such tools often lack realistic models for occupant-driven demands, such as appliance and lighting (AL) loads. For community-scale analysis, such AL models must also be able to capture the temporal and inter-dwelling variation to achieve realistic estimates of aggregate electrical demand.

This work adapts the existing Centre for Renewable Energy Systems Technology (CREST) residential energy model to simulate Canadian residential AL demands. The focus of the analysis is to determine if the daily, seasonal, and inter-dwelling variation of AL demands estimated by the CREST model is realistic. An in-sample validation is conducted on the model using 22 high-resolution measured AL demand profiles from dwellings located in Ottawa, Canada. The adapted CREST model is shown to broadly capture the variation of AL demand variations observed in the measured data, however seasonal variation in daily AL demand behaviour was found to be under-estimated by the model. The average and variance of daily load factors was found to be similar between measured and modelled. The model was found to under-predict the daily coincidence factors of aggregated demands, although the variance of coincident factors was shown to be similar between measured and modelled. A stochastic baseload input developed for this work was found to improve estimates of the magnitude and variation of both baseload and peak demands.

Keywords: domestic electricity use; energy demand modelling; distributed generation; embedded energy; bottom-up modelling; appliance and lighting

1. Introduction

Interest in distributed generation (DG), or embedded generation, continues to grow in both the power infrastructure and building energy fields. DG systems represent a paradigm shift in electrical infrastructure design by situating generation systems near the consumer, reducing transmission losses and potentially improving power quality in the transmission and distribution system (Short 2003). The proximity of DG to the load also provides greater potential for cogeneration, where excess thermal energy from electricity generation may be used to offset building thermal demands. In order to optimally design DG systems, accurate knowledge of the electrical consumer loads is needed (Paatero and Lund 2006). Low-voltage residential networks are especially challenging for DG design and planning, since these types of loads tend to be both stochastic and diverse (Dickert and Schegner 2010).

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Ideally, residential electrical demand profile measurements would be taken directly from a community considering DG for planning and design of the system. Such data acquisition campaigns are often costly, and require long monitoring periods to capture seasonal variations in demand behaviour (Saldanha and Beausoleil-Morrison 2012). There are however, published measurements in the literature which may be used as reasonable estimates for demand analysis. For example, Parker (2003) analysed data from a utility load research project. Detailed total and end-use electrical load data collected from 204 residential dwellings located in Florida, US at a 15-minute resolution. Electricity end-uses monitored include space heating, cooling, domestic hot water (DHW), dryers, cooking, and swimming pools. Firth et al. (2008) monitored the 5-minute whole-house average power consumption of 72 residential dwellings located in 5 different regions in the UK for two years. Saldanha and Beausoleil-Morrison (2012) and Johnson and Beausoleil-Morrison (2017) measured the annual electrical consumption of 22 single-detached (SD) and double/row (DR) houses located in Ottawa, Canada at a 1-minute resolution. Kolter and Johnson (2011) created a database of monitored whole-house, individual circuit, and plug level electrical energy consumption data from ten Boston, USA homes with a combined total of 119 monitored days.

In the absence of measured data, analysis of residential energy demand may be realized through the use of various modelling techniques. One approach is building performance simulation (BPS) tools. Armstrong et al. (2009) stated that BPS tools are ideal for assessing the performance of distributed energy systems, especially those employing cogeneration. Their reasoning was that BPS tools use well-defined physical thermodynamic and heat transfer relationships to calculate temporal thermal demands. Several BPS tools include explicit models of building HVAC equipment using analytical or empirical methods.

However, BPS tools lack models for estimating the occupancy-driven loads, such as appliance and lighting (AL) demands (Armstrong et al. 2009; Swan and Ugursal 2009). At a community-scale, occupancy-driven loads vary both temporally and between dwellings. Under or over-estimation of load diversity during analysis leads to over or under-estimation of aggregate peak demand, respectively. For residential AL demands, there are several modelling techniques in the literature which may be applied to BPS tools and community-scale energy analysis.

1.1. *Review of appliance and lighting models*

Several AL modelling techniques may be broadly classified as 'bottom-up'. Bottom-up methods rely upon statistical or engineering principles to estimate residential energy consumption (Swan and Ugursal 2009). Statistical approaches utilize historical data and regressions to estimate the energy consumption of a particular end-use, such as either appliances or lighting. Engineering approaches estimate end-use energy consumption by using power ratings and equipment usage data, and/or physically based thermodynamic and heat transfer relationships.

Bottom-up AL models may be further categorized as either explicit or implicit-occupancy models. Explicit-occupancy models, referred to by Flett and Kelly (2017) as occupancy-to-demand models, are driven by inputs or estimates of explicit occupant presence in dwellings at each timestep. Alternatively, implicit-occupancy models often rely on AL usage statistics to determine when AL devices are turned on. The explicit presence of occupants is not determined for the dwelling.

Walker and Pokoski (1985) developed an explicit-occupancy bottom-up model for residential energy load shapes based on occupant 'availability' and 'proclivity'. Probability functions for occupant availability at home were determined for weekdays and weekends. The model uses the probability of availability functions with a Monte-Carlo method to estimate actual availability in a dwelling or group of houses. The behaviours and actions of available occupants are then determined using a similar method, instead of using sets of proclivity functions. These functions include the likelihood of operating clothes washers and having a meal. Capasso et al. (1994) built upon this principle, developing a bottom-up model using sets of 'behavioural' and 'engineering' functions. The behavioural functions included histograms for occupant availability, appliance usage percentage distributions, number of available human resources (number of available hands, eyes, and ears to perform tasks), and appliance ownership. Engineering functions included information on appliance cycle time and power demand. Capasso et al. (1994) also used a Monte-Carlo method to determine individual appliance ON/OFF cycles.

Other researchers have adopted a similar approach to residential energy demand modelling. For example, Richardson et al. (2010) developed the open-source Centre for Renewable Energy Systems Technology (CREST) demand model[1], available under the GNU General Public License 3. The CREST model determines occupancy at ten-minute timsteps using the high-resolution occupancy model developed previously by Richardson, Thomson, and Infield (2008). A first-order Markov-Chain is used to determine the number of active occupants in the dwellings. The transition probability matrices (TPMs) were derived using UK TOU survey data, where the time-of-use (TOU) data was subdivided by weekday or weekend, and number of dwelling residents. The CREST model explicitly models each appliance and lighting fixture demand. Electric space heating was also included in the CREST version published by Richardson et al. (2010). Trigger ON events for appliances are determined from the number of available occupants, whether it is a weekday or weekend, and specific occupant activity probabilities for the particular time of day (e.g. cooking). Each lighting fixture is explicitly modelled using the method developed previously by Richardson et al. (2009). The CREST model incorporated 'calibration scalars', which allowed users to tune model output to desired average annual AL consumption per dwelling.

Richardson et al. (2010) validated their model using 22 measured annual whole-dwelling electrical consumption profiles collected from UK dwellings at a one-minute resolution. All measured dwellings did not contain electric space heating equipment, and the validation of the CREST model was limited to the AL demand component of the model. Richardson et al. (2010) found annual consumption distribution, annually-averaged daily profiles, and load diversity calculated for 22 demand profiles modelled in the CREST had good agreement with the measured data. However, Richardson et al. (2010) noted that the CREST model tended to under-estimate the baseload demand and seasonal variation seen in the measured data.

Examples of implicit-occupancy bottom-up models include the work of Paatero and Lund (2006). They used measured electrical consumption from Finnish households to model residential appliance use. The model was composed of two components. First, the daily 'social random factor' was determined for the entire group of dwellings to be modelled. When analysing their measured data, Paatero and Lund (2006) observed a daily fluctuation in energy consumption which was not explained by seasonal and weekday/weekend variation. They attributed this variation to a social random factor, and found that it followed a normal distribution. They attributed this variation to fluctuations in weather and entertainment experienced simultaneously by all dwellings. The second component of the model randomly assigns appliance stock to each household based on published appliance saturation levels, and for each timestep, an appliance ON event probability is determined using seasonal, hourly, mean daily starting frequency, and random social factor. Paatero and Lund (2006) compared output for 10,000 simulated dwellings with 702 measured Finnish dwellings, and found that hourly differences between the mean-daily load profiles were generally below 3%.

Other models use the implicit-occupancy approach, such as the Canadian residential electric profiles model of Armstrong et al. (2009). Their model used appliance specific time-of-use (TOU) curves from Pratt et al. (1989), usage, and power characteristics to stochastically determine demand profiles for lighting and appliances. A 'chance factor' was included in the model to enable it to be calibrated to achieve desired annual energy consumption targets. They validated their model against 2.5 years worth of data collected by Hydro Québec, and found that the measured profiles exhibited more repetitive behaviour compared to modelled. They also found that the generated profiles had lower base load consumption compared to the measured values. Yilmaz, Firth, and Allinson (2015) used sub-metered data from 5,000 appliances located in 250 UK dwellings to develop their appliance demand model. The measured data was used to derive trigger ON probabilities for each appliance, frequency of usage, distributions of cycle durations, and distributions of

[1]The CREST demand model is publicly available for download at `http://www.lboro.ac.uk/research/crest/demand-model/`

power consumed. This data was used to stochastically determine the demand profiles of residential appliances.

Fischer, Härtl, and Wille-Haussmann (2015) also used an implicit-occupancy bottom-up approach in their synPRO model for AL energy consumption in the German residential sector. AL stock and usage were defined using socio-economic characteristics such as dwelling type (single or semi-detached, etc.), and number and ages of occupants. These characteristics were combined to define 14 separate dwelling classes. Fischer, Härtl, and Wille-Haussmann (2015) performed an out-of-sample validation for seven of the classes using 430 dwelling measurements from cities in Germany at a one-hour resolution. They found the synPRO had accuracy around 91% for mean yearly, monthly, and daily energy consumption. They also stated that the current version of synPRO partly covered the intra-group variation and weekend noon peak loads.

There are also residential energy demand models which do not fit neatly into either the implicit or explicit-occupancy definition. Widén and Wäckelgård (2010) utilized TOU to define 9 different activity states, including sleeping, dish washing, and computer. The TOU survey data were used to construct sets of transition probabilities for each timestep modelled. A first order Markov-Chain approach was then used to estimate what activities each occupant were engaged in throughout the day. Each activity had an associated ON electrical demand profile, which was used to convert from activity to electrical consumption profiles. Widén and Wäckelgård (2010) found that this simplified method of activity to power demand conversion could produce realistic demand patterns, and required lower-resolution input data.

1.1.1. Applications in Community Energy Simulation

Several of the aforementioned bottom-up AL and residential modelling techniques have been adopted to community-scale energy models. Marszal-Pomianowska, Heiselberg, and Larsen (2016) and Wagner, Waniek, and Häger (2016) both used implicit-occupancy approaches in their residential demand models. Marszal-Pomianowska, Heiselberg, and Larsen (2016) developed a community-scale energy model which included HVAC energy consumption. Occupants were defined as interested, neutral, and disinterested in electricity use/savings, and each type had an associated scalar multiplier which was applied to the frequency of use for the 35 different appliances considered in the model. Lighting demand was modelled using the method previously developed by Stokes, Rylatt, and Lomas (2004). To validate their model, Marszal-Pomianowska, Heiselberg, and Larsen (2016) performed an out-of-sample validation using 89 dwelling measurements at one-hour resolution, and 16 dwelling whole house and heat pump energy consumption at a five-minute resolution. They found the model represented the diversity of demand among dwellings, however individual dwelling high-end energy consumption was under-predicted by the model. Additionally they found mean annual energy consumption estimated by the model agreed with relevant Danish statistics.

Wagner, Waniek, and Häger (2016) developed a model for aggregate residential electrical demands for designing distribution systems. They considered 13 appliances, each with its own representative load profile. Trigger ON events for non-baseload appliances were modelled using a first-order Markov-Chain technique. Wagner, Waniek, and Häger (2016) also included electrical demand for instantaneous DHW. Validation of the model was conducted by comparing simulated aggregate dwelling demands to relevant German standard profiles. They found that the model tended to over-estimate demands from 00h00 to 06h00, and under-estimate demand between 06h00 and 22h00. They stated the discrepancies were likely due to the 15-minute resolution and relatively small number of appliance classes defined. Wagner, Waniek, and Häger (2016) also considered the annual energy consumption for each appliance class, and found the contribution of each class to whole-dwelling consumption was similar to the portions published by government statistics for average dwellings in Germany. Additionally, the annual average dwelling energy consumption estimated by the modelled differed by 3% compared to German statistics.

Nijhuis, Gibescu, and Cobben (2016) and Flett and Kelly (2017) both used explicit-occupancy approaches in their community energy demand models. Similar to Wagner, Waniek, and Häger

(2016), Nijhuis, Gibescu, and Cobben (2016) developed a model of aggregate whole-dwelling electrical demands. Occupancy was determined using a first-order Markov-Chain and TPMs derived from Dutch TOU data at a 15-minute resolution. Heating and cooling loads were also included in their aggregate demand model. Validation was performed using smart meter data from 100 Dutch dwellings, at a 15-minute resolution, and two transformer data sets connected to 107 and 94 dwellings at a ten-minute resolution. They found the variation and general behaviour of the measured data was largely captured by the model.

Flett and Kelly (2017) used a higher-order Markov-Chain occupancy model developed previously by Flett and Kelly (2016) in their explicit-occupancy domestic electricity demand model. The higher-order approach considers the previous occupant state as well as the duration of an activity when estimating future occupancy. To better capture the diversity of occupancy characteristics, Flett and Kelly (2016) developed separate TPMs based on occupant, household, and day types. To model appliance demands, Flett and Kelly (2017) used two-minute resolution individual appliance measurements from 251 dwellings in the UK, monitored for at least one month. They additionally had 26 full annual electrical consumption measurements at a ten-minute resolution. Flett and Kelly (2017) used a differentiated, probabilistic, bottom-up approach to simulate residential electrical demands. The appliance modelling approach was event based, where the number of appliance triggers on events is determined for the day, rather than the time of occurrence of the events. In contrast, models such as the CREST by Richardson et al. (2010) use per-timestep probabilities to model trigger ON events. Flett and Kelly (2017) performed an in-sample validation demonstrating that the model was capable of replicating the variable demand behaviours seen in the measured data used for calibration. They stated that initial analysis with two small out-of-sample UK data sets also showed similar performance as the in-sample validation.

Other researchers directly adopted published AL demand models into their community-scale energy models. Muratori et al. (2013) used the modelling technique of Widén and Wäckelgård (2010) to simulate the occupant driven demands, developing their TPMs using the 2003-2009 American Time Use Survey (ATUS). Building HVAC demands were modelled using first law energy balances, expressing the building envelope using overall thermal resistance theory from ASHRAE Fundamentals (ASHRAE 2009) and mechanical equipment efficiencies and ratings. They performed both an in-sample and out-of-sample validation, integrating their model demands to hourly profiles for comparison with the metered data. Muratori et al. (2013) compared the distribution and variance between the measured and modelled sets, and found no statistically significant differences.

Baetens and Saelens (2016) adopted the CREST appliance load model of Richardson et al. (2010) in their 'Stochastic Residential Occupant Behaviour', or StROBe, model. To determine occupancy, Baetens and Saelens (2016) characterized three occupancy states: present and awake, present and asleep, or absent. Belgian TOU data was sub-grouped using agglomerative hierarchical clustering and the Levenshtein distance as the distance metric to define seven clusters of TOU data. Each occupant of a dwelling is defined as full-time, part-time, retired, or minor, and allocated to a cluster. Transitions of occupancy are determined using event and survival time densities, defined for weekdays, Saturdays, and Sundays. The StROBe model additionally models lighting loads using the method of Widén, Nilsson, and Wäckelgård (2009), internal heat gain from occupants, heating setpoints, and DHW draws. When evaluating the epistemic (systematic) uncertainty of the StROBe model, Baetens and Saelens (2016) found that the model under-estimated average annual electricity consumption. They noted that bottom-up AL models often under-estimate load due to the exclusion of some appliances. They also stated that the annual consumption used for comparison also included demands from pumps and fans. Baetens and Saelens (2016) also determined that the simultaneity (coincidence) factors of StROBe electrical and DHW draws was found to have good agreement with pertinent reference standards.

1.2. *Research objectives and outline of paper*

When evaluating the performance of appliance and lighting models, researchers often examine mean or annually averaged metrics. It is sometimes unclear that the variation of performance metrics, such as daily energy consumption, are also being captured by the model. The current work adopts the CREST model developed by Richardson et al. (2010) to simulate the residential AL demands of Canadian single-detached (SD) and double/row (DR) dwellings. Richardson et al. (2010) had demonstrated previously that the CREST model is capable of capturing the majority of daily and inter-dwelling variations of AL demand that exists in practice.

The objective of the work is to determine if the adapted CREST model is capable of not only reproducing the nominal performance characteristics, such as daily load factors and energy consumption, seen in practice in Canada, but also the variation of those metrics between dwellings and throughout the year. Models capable of achieving both the nominal characteristics as well as the variation seen in practice would be a valuable tool for analysis of both individual dwelling energy consumption as well as aggregate community demands.

To analyse and validate the CREST model, 22 one-minute resolution annual AL demand measurements collected previously by Saldanha and Beausoleil-Morrison (2012) and Johnson and Beausoleil-Morrison (2017) are used for comparison. Richardson et al. (2010) similarly used high-resolution whole-dwelling electrical demands from 22 UK dwellings to validate the CREST model. This high-resolution provides an opportunity to evaluate the model's capability of simulating momentary peak demands and short-term variations seen in practice. Several of the AL models found in the literature use lower resolution data for validation, sometimes collected over short time periods, from different geographic regions, and not during the same time of the year. The measured data used here is from a similar geographic location monitored over coincident time periods.

This paper is divided into several sections. Section 2 provides a brief summary of the architecture and methodologies used in the CREST model. Relevant data sources for modelling Canadian residential dwellings are also described in this section. Richardson et al. (2010) had previously noted that the CREST model tended to under-predict night-time (baseload) demands. To improve night-time energy demand estimation in the current work an unattributed constant baseload demand is stochastically determined for each simulated dwelling, and is described in Section 2.5.

Section 3 discusses the in-sample validation carried out using the available measured data. Performance characteristics considered in the validation include mean daily AL demand profile, distribution of mean daily AL energy consumption by weekday and month, distribution of dwelling daily load factors, and distribution of aggregate demand daily coincidence factors. Section 4 then evaluates the impact of the stochastic baseload input on model performance. The final two sections of the paper then provide conclusions and recommendations.

2. Model summary

The summary presented here is based on version 1.1 of the CREST model. This was the version of the model available at the beginning of this work and was adapted for Canadian dwellings. Since then updates have been published to the CREST model. McKenna, Krawczynski, and Thomson (2015) extended the previous occupancy model of Richardson, Thomson, and Infield (2008) by defining four occupancy states: not home and inactive, not home and active, at home and inactive, and at home and active. The state of occupants were determined using a first-order Markov-Chain technique. McKenna and Thomson (2016) later added additional modelling domains to the CREST model, including low-order building envelope modelling, DHW consumption, and solar thermal collectors. For the current work however, solely the AL modelling capabilities of the CREST model were of interest and were present in version 1.1.

2.1. *Model structure*

This section provides a brief summary of the CREST model, as presented by Richardson et al. (2010). The general structure of the model is described, and the pertinent underlying methods are highlighted. The current work primarily deals with the determination of inputs and modifications to the CREST model occupancy and appliance modules, and brief descriptions of these modules are provided below. Details of the lighting module is provided by Richardson et al. (2009). The lighting module requires outdoor solar irradiance data for each simulation timestep. For the current work, this value is assumed to be the global horizontal solar irradiance at the dwelling site.

2.1.1. Occupancy module

Stated previously in Section 1.1, the CREST model uses an explicit-occupancy approach. The occupancy module was developed by Richardson, Thomson, and Infield (2008), and uses a first-order Markov-Chain technique to determine the number of active occupants at each timestep. The TPMs were derived from the United Kingdom Time Use Survey (ONS 2003), and separate TPMs were defined based on the number of occupants in a dwelling in the source data, as well as day type *d*. Richardson, Thomson, and Infield (2008) divided day types as weekday and weekend.

Statistics Canada has been conducting time-use surveys as a part of the General Social Survey (GSS) Program since 1986 (Statistics Canada 2016). Information is collected using a retrospective 24-hour diary provided by respondents. Respondents are asked about what activities they were engaged in starting at 04h00, as well as where they were. The current work extracts occupancy and activity data from the GSS, Cycle 24, 2010: Time-Stress and Well-Being Survey (Statistics Canada 2010). Sampling was conducted in 6 waves between January and December 2010. The GSS 2010 survey contains 15391 individual diaries sampled from across Canada. Demographic information is also provided with each diary, providing information such as household size, location, ages, income, etc. The GSS 2010 also asked respondents if they were engaged in simultaneous activities, such as listening to the radio while cleaning the house. Up to three simultaneous activities were recorded.

The diaries were sorted by household number, from one to five dwelling residents, and by weekday and weekend. The corresponding number of diaries for each sub-category are summarized in Table 1. Richardson, Thomson, and Infield (2008) had been able to construct household occupancy profiles by superimposing individual occupancy profiles provided from the same dwelling. Unlike the UK survey however, the GSS 2010 does not provide information on whether diaries were collected from the same household. Household profiles were constructed by randomly combining diaries from dwellings with the same number of residents. For dwelling sizes two to five, and weekday and weekend day types, 5000 random combinations of individual occupancy profiles were generated. From the household profile, the TPMs were developed using the method described by Richardson, Thomson, and Infield (2008).

Table 1. Number of 24-hour diaries from the GSS 2010

Number of dwelling occupants	**Day type** Weekday	Weekend
one	2723	1061
two	4113	1675
three	1692	643
four	1630	657
five	615	239

2.1.2. Appliance module

Richardson et al. (2010) noted that usage of appliances are dependent on the time of day as well as the presence of occupants. To recognize this in the CREST model, Richardson et al. (2010)

re-analyzed the UK TOU survey data, and developed sets of 'activity' probability distributions, $P_{A,d}\left(t, N_{occupants}\left(t\right)\right)$, for different activities A and day types d, as functions of both the time of day, and number of active $N_{occupants}$ determined previously in the occupancy module. For the current study, the activity types A considered were: cooking, watching television, laundry, house cleaning, ironing, washing/dressing, computer use, and other. The 'other' activity implies that the probability of a trigger ON event does not vary with time. For appliances that do not conveniently fit into one of the activity categories, and is occupant-dependent to trigger ON, $P_{A,d}\left(t, N_{occupants}\left(t\right)\right)$ is equal to 1.

The GSS 2010 diaries (Statistics Canada 2010) were used to determine $P_{A,d}\left(t, N_{occupants}\left(t\right)\right)$ using the method described by Richardson et al. (2010). Activities in the GSS 2010 were identified with a integer code. Statistics Canada (2010) defined several hundred different acitivity codes. These codes were reviewed and associated with the seven activities considered in the current study.

For each appliance i modelled, the user must specify:

- appliance activity type, A_i;
- if appliance operation is occupant dependent;
- average number of cycles per year, $N_{i,cycles}$;
- cycle length, $t_{i,cycle}$ [min];
- reset delay, $t_{i,reset}$ [min];
- mean ON power, $\bar{Q}_{i,appl,ON}$ [W];
- standby power, $Q_{i,appl,standby}$ [W].

The trigger ON events of each appliance are determined separately for each appliance i. For each timestep t, the probability of appliance i triggering ON, $P_{i,appl,ON}\left(d, t, N_{occupants}\left(t\right)\right)$, is determined based on number of active occupants at time t and day type d using Equation 1:

$$P_{i,appl,ON}\left(d, t, N_{occupants}\left(t\right)\right) = C_{i,appl} \cdot P_{A,d}\left(t, N_{occupants}\left(t\right)\right) \tag{1}$$

The appliance scalar for appliance i, $C_{i,appl}$, is determined prior to simulation using the inputs for appliance i. The calculation procedure for $C_{i,appl}$ is omitted here for clarity, and the interested reader is directed to Richardson et al. (2010) for additional details.

When appliance i is triggered ON, the CREST model then determines the appliance's power consumption. Prior to simulation, the power demand for appliance i, $Q_{i,appl,ON}$ [W], is randomly determined from a Gaussian distribution with a mean of $\bar{Q}_{i,appl}$ and standard deviation of $1/\bar{Q}_{i,appl,ON}$. Richardson et al. (2010) included this in the CREST to induce variability between dwellings. To determine the appliance power consumption during operation, Richardson et al. (2010) defined two different cycle types in the CREST model: 'simple' and 'complex'.

For simple cycle appliances, the power demand for appliance i is a constant $Q_{i,appl,ON}$ for cycle duration $t_{appl,cycle}$, or until no occupants are active[2]. Complex cycles are associated with appliances such as washing machines and dishwashers, which have varying power demand during its operational cycle. Richardson et al. (2010) incorporated measured profiles of washing machines and washer/dryers into the CREST model to simulate their complex cycle power demands.

Richardson et al. (2010) also incorporated a global appliance calibration scalar, $C_{appl,calibrate}$, in the CREST model. This scalar enables users to tune the CREST model to achieve a specified nominal dwelling annual appliance energy consumption. For each appliance i simulated in each dwelling, $N_{i,cycles}$ is multiplied by $C_{appl,calibrate}$. A separate but similar calibration scalar is also included in the lighting module, $C_{light,calibrate}$, the details of which may be found in Richardson et al. (2009).

[2]Unless appliance is independent of occupancy, or continues to run in the absence of occupants.

2.2. *Appliance & lighting inputs*

Shown in Section 2.1.2, the CREST model requires detailed input information for each appliance explicitly considered in the model. For the current work, 31 appliances were considered and are listed in Appendix A. Several sources were consulted to estimate the appliance inputs. The mean appliance ON and standby power demands, $\bar{Q}_{i,appl}$ and $Q_{i,appl,standby}$, for each appliance i were estimated using recommended values from a local electrical distribution company (Hydro One Networks Inc. 2017), the U.S Department of Energy (DOE) Building America Analysis Spreadsheet for Existing Homes (DOE 2011), and the Lawrence Berkeley National Laboratory (LBNL) Standby Power Summary Table (LBNL 2017).

Mean cycle lengths, $t_{i,cycle}$, and cycles per year, $N_{i,cycles}$, were estimated using the GSS 2010 (Statistics Canada 2010), and the Survey of Household Energy Use (SHEU 2011) from Natural Resources Canada (NRCan 2014). For the current work stove appliances were divided into five separate components: two large and two small ranges, and an oven. Annual stove usage was estimated using SHEU 2011, and $t_{i,cycle}$ and $N_{i,cycles}$ for each stove component was estimated using the Cooking Appliance Use report from LBNL (Klug, Lobscheid, and Singer 2011).

For appliances with complex cycle power demand, measured data was used. The current work identified three appliances with complex cycles: dishwashers, clothes washers, and clothes dryers. Typical dryer and dishwasher cycle power demand profiles were estimated using the plug-load measurements collected by Saldanha and Beausoleil-Morrison (2012) and Johnson and Beausoleil-Morrison (2017). These data sets collectively contain the annual consumption profiles of 5 dryers and 4 dishwashers. Washing machine cycle power consumption was estimated using measurements from a 1990's vintage vertical-axis washing machine. Data was collected at a 1-minute resolution using a Watts Up? PRO ES datalogger (Watts up? 2008).

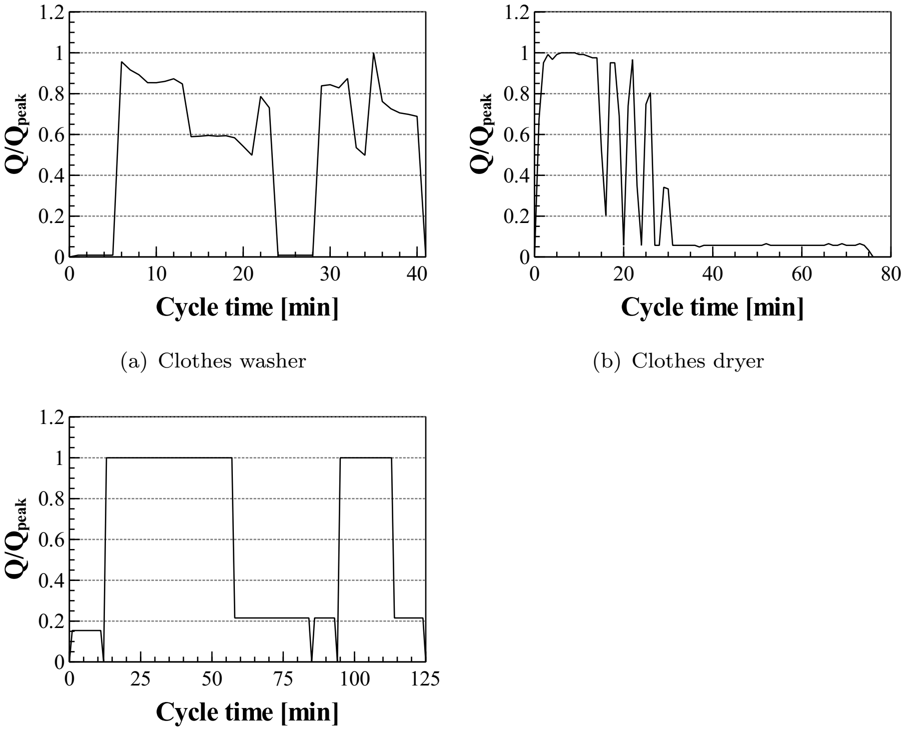
The complex cycles used in the current work are plotted in Figure 1. Each profile is normalized with respect to its peak demand. The user provides a value for $\bar{Q}_{i,appl,ON}$, and the associated complex cycle profile in Figure 1 is multiplied by $Q_{i,appl,ON}$ to determine the time-varying power demand of the appliance.

Each appliance i considered in the CREST model is associated with an activity A_i. Richardson et al. (2010) had defined six activity types: watching TV, cooking, laundry, washing and dressing, ironing, and house cleaning. For each activity, Richardson et al. (2010) developed daily activity profiles which quantified the probability of an activity occurring as a function of time-of-day, number of active occupants, and day type. These activity profiles were derived using the UK TOU data. The current work developed profiles for the six activities defined in the CREST model using the GSS 2010 TOU diaries. Additionally, the activity 'using computer' was defined for the current work.

For the lighting module, average power demand values for residential incandescent, halogen, compact fluorescent lamp (CFL), linear fluorescent (tube), and other (light-emitting diode (LED)) lamp types were extracted from the DOE 2010 U.S. Lighting Market Characterization Report (Ashe et al. 2012). The report provides average wattages for each lamp type, as well as average wattages for lamp sub-types, such as general service and reflector halogen lamps. The wattages for each sub-type were used as inputs into the lighting module.

2.3. *Appliance & lighting dwelling stock allocation*

Richardson et al. (2010) used appliance stock distribution data to allocate dwelling appliances in the CREST model. For the current work, the majority of dwelling appliance stock was drawn directly from the Canadian Single-Detached and Double/Row Housing Database (CSDDRD), developed by Swan, Ugursal, and Beausoleil-Morrison (2009). The CSDDRD is comprised of over 17,000 detailed records for dwellings from across Canada, sub-grouped by dwelling type (SD or DR) and location. Each record contains detailed information on the building envelope, HVAC system, as well as a selective inventory of the dwelling's stock of large and small appliances. The CREST model was



(a) Clothes washer

(b) Clothes dryer

(c) Dishwasher

Figure 1. Normalized complex appliance cycle profiles

integrated into the CSDDRD for the current work. The user specifies a record, or list of records, in the CSDDRD for which they wish to generate annual AL demand profiles for. The number of occupants in the dwelling and appliance stock are then drawn directly from the CSDDRD.

One limitation of the CSDDRD is that it has not been updated in over a decade to reflect technological and economic changes. For example, penetration rates of gaming consoles were included in SHEU 2011, but were not reported in the CSDDRD. To address this limitation, a stochastic method for assigning these new devices similar to the method used by Richardson et al. (2010) was used. Randomly assigned devices included gaming consoles, television receiver boxes, and printers. Penetration levels of these appliances were defined separately for five Canadian regions: Atlantic Canada, Québec, Ontario, Prairies, and British Columbia. The original Richardson et al. (2010) also included appliances that are not reported in either the CSDDRD or SHEU 2011; specifically irons, kettles, and vacuums. For those appliances, the UK penetration rates reported by Richardson et al. (2010) were used. No data was available for hair dryer ownership. In the absence of data it was assumed 90% of dwellings have a hair dryer.

The GSS 2010 data indicated that televisions are used frequently by occupants throughout evening periods. The current implementation of the CREST model used available data to take a detailed approach to television power consumption. The CSDDRD provides the total number of colour and black & white televisions in each dwelling. For the current implementation of the CREST model, the total number of televisions in the dwelling are determined directly from the CSDDRD, and for each unit the type of television is determined from stock distributions provided in SHEU 2011. Five television types were considered based on the information provided in SHEU 2011: Regular, plasma, LED, LCD, DLP, and projector. Input parameters for each television type were identical with the exception of $\bar{Q}_{i,appl}$. Values of $\bar{Q}_{i,appl}$ for each type were estimated from Hydro One Networks Inc. (2017) and DOE (2017), and are provided in Appendix A.

2.4. *Cold appliance modelling*

Cold appliances, such as fridges and freezers, largely form the baseload for residential electrical demand. The CREST model defined four types of cold appliances[3], each with a defined set of inputs. A different approach was used in the current implementation of the CREST model to capture the diversity of cold appliance efficiencies found in the Canadian residential stock. Detailed information on cold appliance unit energy consumption (UEC) values were collected from the Energy Consumption of Major Household Appliances Shipped in Canada: Trends for 1990-2010 report from NRCan (2012). This report lists average UEC values of cold appliances by type and year they were shipped in Canada.

For the current CREST model implementation three cold appliance types were considered: refrigerator, upright freezer, and chest freezer. For each type, $N_{i,cycles}$, $t_{i,cycle}$, and $t_{i,reset}$ values are defined by the user. For the current work these values were estimated from Richardson et al. (2010) and Armstrong et al. (2009), and are provided in Table 2. Dwelling cold appliance stock and sizes are drawn directly from the CSDDRD, and cold appliance vintages are randomly selected from vintage distributions estimated from the SHEU 2011.

Table 2. Cold appliance inputs

Cold Appliance	**Input**		
Type	$N_{i,cycles}$ [cycles/yr]	$t_{i,cycle}$ [min]	$t_{i,reset}$ [min]
Refrigerator	6116	35	35
Upright Freezer	6116	20	40
Chest Freezer	6116	14	56

For refrigerators, the *UEC* is read directly from Table A.13 in NRCan (2012). For freezers, NRCan (2012) provided five different classifications: upright manual defrost, upright auto defrost, chest, compact upright, and compact chest and other. The type of freezer is randomly selected from distributions by vintage provided in Table A.17 in NRCan (2012). The *UEC* for the freezer is then read directly from Table A.22 in NRCan (2012). The *UEC* and other inputs are then used to determine $Q_{i,appl,ON}$ for each cold appliance in the dwelling us the equation:

$$Q_{i,appl,ON} = \frac{UEC}{N_{i,cycles} \cdot t_{i,cycle}} \cdot 60,000 \quad (2)$$

where 60,000 is a unit conversion factor.

2.5. *Dwelling baseload*

When Richardson et al. (2010) compared AL profiles generated by the CREST to measured profiles, they noted that the CREST model tended to under-predicted night-time (baseload) AL demands. A simplified approach was taken in the current work to address these discrepancies. Widén et al. (2009) had found that using TOU surveys to derive their electrical consumption profiles captured the majority of electricity end-uses, but neglected to capture a nearly constant unspecified demand seen in their measured data. To address this discrepancy, Widén and Wäckelgård (2010) included an 'additional constant load' in their demand model. A similar approach was adopted here, where each dwelling AL demand generated also included a stochastically determined constant baseload demand.

This stochastic baseload was incorporated into the appliance module. Two global variables are used in determining baseload demand for each dwelling: mean baseload demand $\bar{Q}_{baseload}$ [W], and baseload standard deviation $Q_{baseload,std.dev}$ [W]. For the current study these values were estimated

[3]Chest freezer, fridge freezer, refrigerator, and upright freezer

from the measured data of Saldanha and Beausoleil-Morrison (2012) and Johnson and Beausoleil-Morrison (2017) to be 250 W and 70 W, respectively. For each dwelling AL demand generated, the dwelling baseload is randomly selected from a Gaussian distribution. The baseload is then added to the aggregated AL demands determined by the CREST model. The appliance module calibration scalar, $C_{appl,calibrate}$, is not applied to the baseload inputs since the scalar operates on the number of annual cycles of appliances and does not impact constant demand appliances.

3. Model validation

Richardson et al. (2010) validated the CREST model against 22 measured one-minute resolution whole-dwelling demands from volunteers in the UK. Richardson et al. (2010) stated that none of the dwellings had electric heating systems installed. Each of the 22 dwellings was modelled in the CREST, and characteristics of both the annual measured and modelled AL demands were compared. Richardson et al. (2010) noted a few discrepancies, namely an under-prediction of night-time demand, variation of dwelling annual demands, and under-prediction of seasonal variation. These differences were largely attributed to a lack of data pertaining to, for example, socio-economic factors, multi-tasking of activities, seasonal behaviour of occupants, and attitudes towards energy conservation. Richardson et al. (2010) found the CREST model was particularly good at capturing the time coincidence and diversity of AL demands amongst dwellings. A difference of 1% in diversity factors was found between the data, and both sets of AL demand profiles tended towards the same after diversity maximum demand (ADMD).

For the current implementation of the CREST model, the annual one-minute resolution AL demand measurements from Saldanha and Beausoleil-Morrison (2012) and Johnson and Beausoleil-Morrison (2017) are used for validation. (Saldanha and Beausoleil-Morrison 2012) collected measurements from eight SD and three DR volunteer dwellings in Ottawa, Canada, between 2009 and 2010. Johnson and Beausoleil-Morrison (2017) collected data from an additional eleven DR dwellings in Ottawa, Canada between 2011 and 2012. The AL demands were determined from whole-house measurements by subtracting the sub-metered measurements of the HVAC equipment.

The validation of the CREST implementation performed here differs from the validation performed by Richardson et al. (2010). An in-sample validation is performed, since both the average annual AL demands, and baseload demands, of the measured validation set were used as model inputs and for calibration. Additionally, the measured dwellings from Saldanha and Beausoleil-Morrison (2012) and Johnson and Beausoleil-Morrison (2017) could not be modelled directly, since insufficient information is provided pertaining to the dwelling's small appliance stock. Instead several modelled profiles are generated, and 22 are paired to the measured profiles based on dwelling annual AL consumption characteristics. The calibration of the CREST model and development of the modelled validation set are described below.

3.1. *Calibration*

Stated previously in Section 2.1.2, the lighting and appliance modules require the user to provide module calibration scalars, $C_{light,calibrate}$ and $C_{appl,calibrate}$, respectively. Module calibration scalars were determined separately for SD and DR dwellings in Ontario Canada. Each module required a calibration target, corresponding to the desired average annual energy consumption per dwelling. For the lighting module, these targets were determined from the Comprehensive Energy Use Database (CEUD) (NRCan 2015). The average annual lighting energy consumption targets for SD and DR dwellings were 1064 and 719 kWh/year/dwelling, respectively. The CEUD also provides estimates for appliance energy consumption, but does not disaggregate between electrical and other fuel types. Instead, the appliance energy targets were estimated by subtracting the average annual lighting consumption from the average annual AL consumption determined from the measured profiles. SD and DR dwelling appliance calibration targets were assumed to be 5759 and 3583 kWh/year/dwelling.

Calibration for each dwelling type was performed by randomly selecting 377[4] Ontario dwellings from the CSDDRD. Annual AL profiles were generated for each dwelling at a 1-minute timestep using the modified AL model. The calibration scalars were iteratively adjusted until the absolute percentage error between the model output and target was below 1%. Once iterations were terminated all Ontario single-detached and double/row CSDRRD dwellings[5] were modelled, and the percentage error of the model-predicted average annual energy consumption for each module and dwelling type are provided in Table 3.

Table 3. Average annual energy consumption percentage errors

Dwelling type	**CREST module** Lighting	Appliance
SD	4.6%	1.5%
DR	1.8%	2.1%

3.2. *Modelled validation set*

To produce the modelled AL demand validation set annual AL demand profiles were generated for all Ottawa, Canada SD and DR records in the CSDDRD, corresponded to 811 and 260 records, respectively. Each measured AL demand profile was paired to a modelled profile which had a minimum weighted difference of annual AL energy consumption, annual baseload demand[6], and annual peak demand. Annual AL energy energy consumption was assumed to be the most important characteristic, and was assigned a weight of 0.7. The annual baseload and peak demands were assigned weights of 0.2 and 0.1, respectively. Baseload was given a higher weight since the influence of the adding the baseload input, described previously in Section 2.5, was of interest for this work. These related pairs of AL demands were used to assess the capability of the CREST model implementation to replicate the temporal and inter-dwelling variations in AL demand. Figure 2 illustrates the distribution of the measured and modelled AL demand profile's annual energy consumption, baseload, and peak demand.

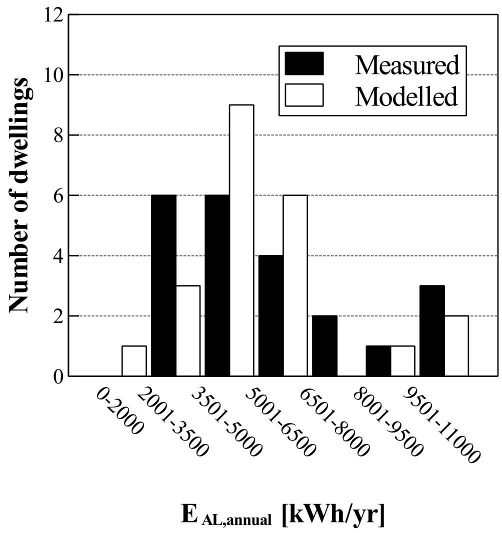
3.3. *Results of in-sample validation*

The measured and modelled validation sets described above were used to perform the in-sample validation of the CREST model. To characterize model performance and behaviour, several metrics commonly used in power distribution analysis were determined and compared for the measured and modelled demand profiles. It is important to note that measured data used for validation is relatively small, and since data collection was voluntary it may be biased. Nonetheless, the measured data is of high resolution and spans an entire year for each sample.

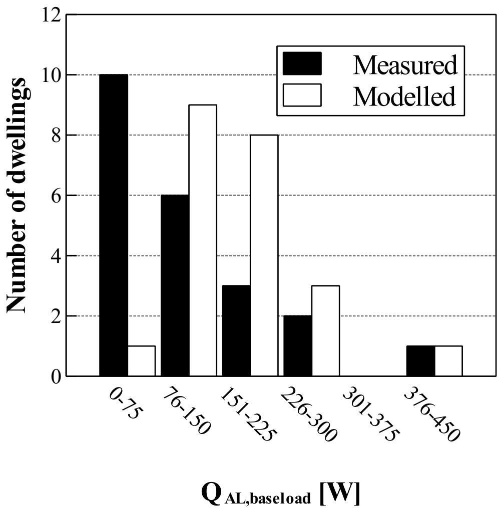
3.3.1. Annual mean daily demand profile

Figure 3 plots the weekday and weekend annual mean daily demand profiles for both the measured and modelled validation sets. Each profile in Figure 3 represents the average over all 22 profiles. The profiles were smoothed using a simple moving average at 15-minute intervals. To express the variation of AL demand for each period of the day, the interquartile range (IQR) of the demands

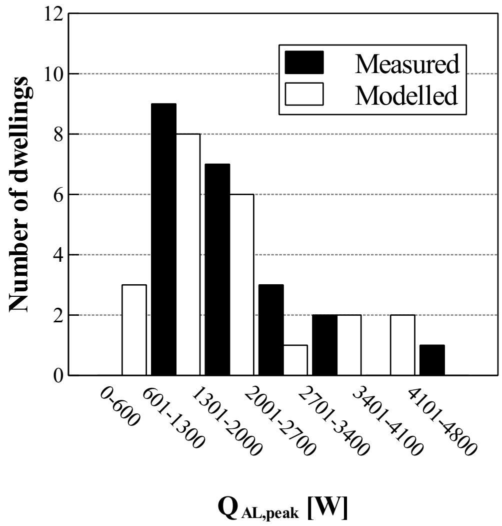
[4]Minimum number of samples required for 95% confidence in large populations
[5]The CSDDRD contained 5404 and 1231 SD and DR records for Ontario, respectively.
[6]Baseload characterized as 5th percentile of AL demand, and peak as 95th percentile



(a) Annual consumption



(b) 5th percentile of the load

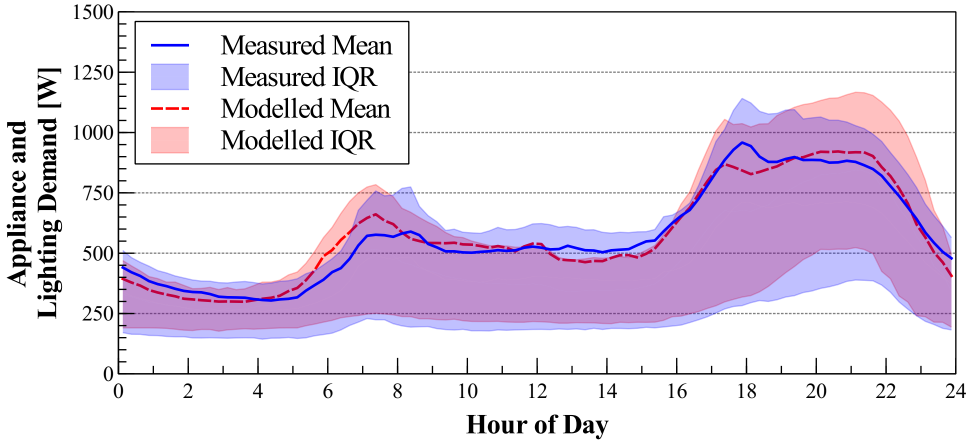


(c) 95th percentile of the load

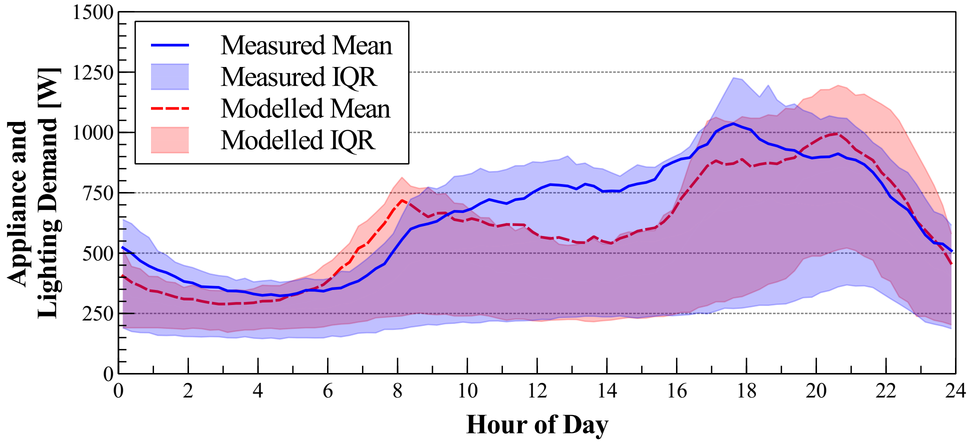
Figure 2. Distribution of annual appliance and lighting load parameters for the measured and modelled sets

are plotted as the shaded regions in Figure 3. The IQR was used as to not exaggerate the variation of the AL demand, but rather illustrate the more typical variation of the demand.
The weekday mean measured and modelled profiles in Figure 3(a) are shown to follow a similar trend, although there are some notable differences. The modelled morning peak demand occurs between 07h15 and 07h30, whereas the measures profile exhibits two morning peaks at 07h15-07h30 and 08h15-08h30. The presence of two peaks in the measured profile suggests behavioural differences between dwellings (i.e. some households starting their day at 07h00, while others start at 08h00), which is not obvious in the modelled demand profile.

The occupancy TPMs developed in the current work were derived from Canadian TOU data which was only differentiated by number of household occupants, averaging out occupant behaviours and likely leading to the single morning peak seen in the modelled data. Evening AL demands are shown to be similar, however the measured weekday profile has a distinct peak between 17h45 and 18h00 whereas the modelled show two less prominent evening peaks. To quantify the differences in the weekday mean daily demand profiles, the mean absolute error (MAE) between the profiles were determined and found to be 37 W. This relatively small error suggests that



(a) Weekday profile



(b) Weekend profile

Figure 3. Annual mean daily demand profiles for all 22 demand profiles

the CREST model broadly captures the average daily demand variations observed in the measured data.

The weekend mean profiles in Figure 3(b) have more obvious discrepancies, especially around midday. The MAE between the two profiles were determined to be 98 W however, suggesting that the CREST broadly captures the average daily AL demand variations during weekends. Qualitatively comparing the two profiles, the measured profile in Figure 3(b) has a steady increase in AL demand throughout the day, whereas the modelled mean profile decreases to a minimum during midday before realizing an evening peak.

Seasonal variation of these mean profiles were considered as a possible explanation for the differences in weekend demand. It was noted that the weekend TPMs and activity probability distributions were derived using all weekend diaries in the TOU survey, and were not differentiated by month or season. Conceivably, occupant presence and behaviours will change with the weather. Figure 4 plots the measured and modelled weekend seasonal mean daily demand profiles for summer and winter[7]. For the measured data profiles, there is a visible increase in evening demand likely due to increased use of lighting and entertainment appliances (i.e. TVs). The modelled profiles are shown to be similar for both seasons, with only a nominal increase during the evening likely due to increased lighting demand.

[7]Summer was defined as June 21 to September 22, and Winter from December 21 to March 20.

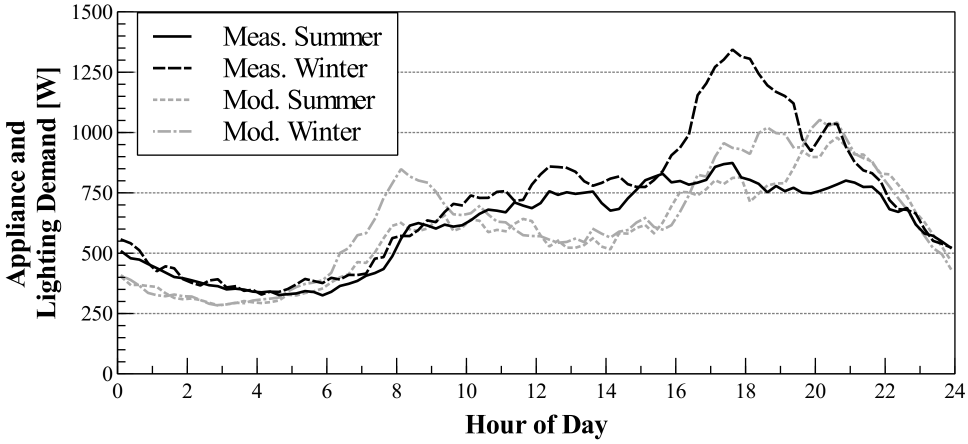


Figure 4. Weekend seasonal mean daily demand profiles for all 22 demand profiles

During the midday periods in Figure 4 however, the measured summer and winter demand profiles are shown to be similar. They are also higher than the modelled profiles, as was the case in Figure 3(b). This suggests that the differences between the measured and modelled weekend midday demands are not due solely to annual aggregation of the TOU weekend diaries. In the absence of plug-level or occupancy information for the measured data, it is difficult to determine the underlying reasons for differences in the weekend demand profiles. Figure 4 suggests however, that greater consideration of seasonal occupant behaviour should be considered in the CREST model.

Lastly, Figure 3 was used to examine the variation of the daily weekday and weekend demands. Qualitatively, the weekday profiles exhibit similar variation in AL demand. During weekend periods however, the CREST model appears to under-estimate the variation in midday demand. To quantify the profile differences the MAE of the IQRs at each 15-minute interval were determined, and found to be to be 77 W and 138 W for weekdays and weekends, respectively. Again, the weekday profiles largely capture the variance of the AL demand, however discrepancies remain for weekend periods.

3.3.2. Seasonal and weekly variation

Richardson et al. (2010) previously examined the seasonal variation of AL demand in 22 simulated UK dwellings, and found that the CREST model had under-estimated the variation compared to measured data. The current work uses a similar approach to Richardson et al. (2010) to evaluate the seasonal variation behaviour of the measured and modelled AL demands. Figure 5 plots the measured and modelled overall mean daily AL demands subdivided by month of the year.

Qualitatively both measured and modelled follow a similar trend of seasonal variation in Figure 5. The measured overall monthly mean daily AL demand varied by 2.6 kWh/day/dwelling during the year. The modelled mean daily demand had a similar variation of 2.5 kWh/day/dwelling, a difference of 4.5% from measured. The peak overall monthly mean daily AL demand occurs in December and November for the measured and modelled, respectively. The minimum mean daily demand occurs in March and July for the measured and modelled, respectively. For the modelled data this was expected, as July is a period of high solar irradiance and low lighting usage. In the absence of plug-level data and occupancy information, it is difficult to speculate why the measured data is a minimum in March.

The overall mean daily AL demands for each day of the week is plotted in Figure 6. Mentioned previously, Richardson et al. (2010) had categorized day types as either weekday or weekend. The implicit assumption is that there is little variation in AL demand within those day types. To test this assumption the daily AL demands were determined for each day and demand profile, and were subdivided based on day of the week. The distribution of the measured and modelled daily

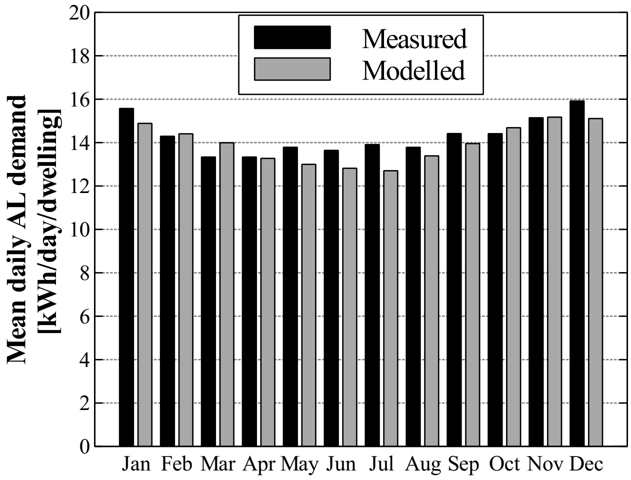


Figure 5. Overall monthly mean daily AL demand

demands are plotted in Figure 6.

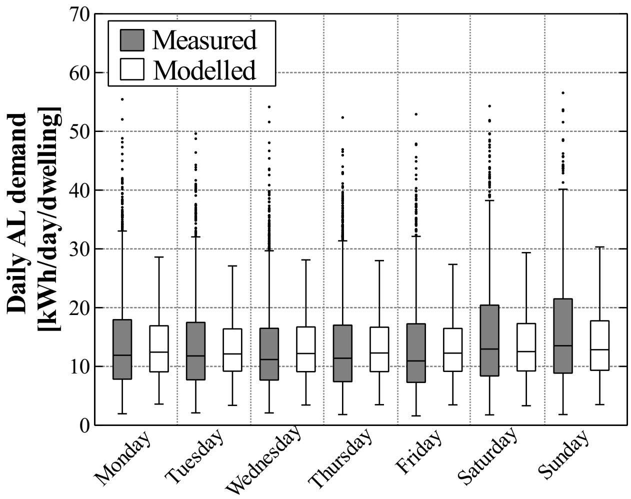


Figure 6. Distribution of weekday daily AL demands

To test the validity of lumping day types into weekday and weekend groups, the distributions of measured daily AL demand within each group were compared. A Brown-Forsythe test was used to compare the variance of daily AL demands. The null hypothesis of this test is that variance is the same for all groups. For the measured weekday and weekend groups in Figure 6, p-values of 0.812 and 0.649 were determined, respectively. This indicates that weekdays have the same daily AL demand variance, and Saturdays and Sundays have the same variance. When both groups were tested together however, the p-value was in the order of 10^{-7} indicating significant differences in variance between weekday and weekend daily AL demands.

A balanced one-way ANOVA test was used to determined if the mean values of the measured daily AL demands in Figure 6 were similar for all weekdays, and if the mean values for Saturday and Sunday were similar. The null hypothesis of this test is that all groups are drawn from populations with the same mean. All weekdays were found to have a similar mean value with a p-value of 0.102[8]. The measured Saturday and Sunday daily AL demands also have a similar mean, with a

[8]Significance level $\alpha = 0.05$

p-value of 0.160. The similarity of both the mean and variance of daily AL demand in the measured profiles giving validity to disaggregating day types as weekday and weekend.

Figure 6 shows that the model under-predicts variation in daily AL demand compared to measured. All measured and modelled weekday groups were compared using the Brown-Forsythe test. The p-value was in the order of 10^{-28}, indicating that the variance is statically different between measured and modelled weekday daily demands. The measured and modelled weekend daily AL demand variances were also found to be different, with a p-value on the order of 10^{-21}. To quantify how different the variances are between measured and modelled, the standard deviations of the weekday and weekend demands were compared. The standard deviations for measured and modelled weekday daily demands were 8.5 and 6.6 kWh/day/dwelling, respectively, yielding a difference of 24.7%. The weekend measured and modelled standard deviations were 9.4 and 7.4 kWh/day/dwelling, respectively, yielding a difference of 23.8%.

3.3.3. Load factors

Richardson et al. (2010) also used the diversity factor and ADMD to analyse the modelled load diversity. The reciprocal of the diversity factor is often referred to as the 'load factor', f_{load}. This factor represents the ratio of the total energy demand during period Δt [h], and the peak power demand over the same period multiplied by Δt, shown in Equation 3:

$$f_{load} = \frac{E_{\Delta t}}{Q_{peak}\Delta t} \tag{3}$$

where $Q_{\Delta t}$ [kWh] is the electrical energy consumed over period Δt, and $\dot{Q}_{peak}$ [kW] is the peak load for Δt. The values of f_{load} can vary between zero and one. At $f_{load} \approx 1$, the load is relatively constant over period Δt, whereas a $f_{load} \approx 0$ would indicate widely varying electrical load (Short 2003). The daily f_{load} values, $f_{load,daily}$, were determined for each modelled and measured profile, and for each day of the year. To calculate $f_{load,daily}$, both modelled and measured profiles were smoothed using a simple moving average at a 15-minute interval. Weekday and weekend $f_{load,daily}$ values for all days and profiles were aggregated separately for the measured and modelled sets, and the range of values are illustrated using box and whisker plots in Figure 7.

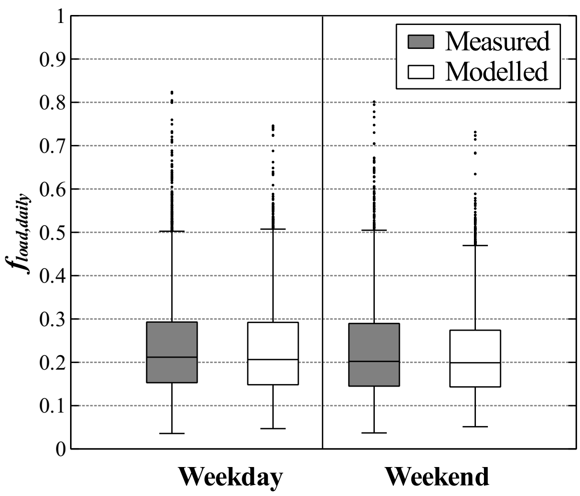


Figure 7. Distribution of measured and modelled weekday and weekend daily load factors

The variation of $f_{load,daily}$ appears to be similar in Figure 7. To test if the variance was statistically similar, the Brown-Forsythe test was used. For weekday $f_{load,daily}$ values, both measured and modelled were found to have similar variance with a p-value of 0.382. For weekend $f_{load,daily}$ values however, the p-value was determined to be 0.003 indicating that the variances of weekend $f_{load,daily}$ values are different between measured and modelled values. The standard deviation of the measured and modelled weekend $f_{load,daily}$ values were determined to be 0.119 and 0.108, respectively.

To compare the mean $f_{load,daily}$ values of the measured and modelled data, a two-sample t-test was used. For weekdays, the t-test p-value was found to be 0.140 suggesting that the mean value of $f_{load,daily}$ is similar between measured and modelled. Again for the weekend periods, the means were found to be statistically different, with a p-value of 0.023. For weekends, the measured and modelled $f_{load,daily}$ mean values were 0.231 and 0.224, respectively.

3.3.4. Coincidence factors

The final parameter considered in the verification study was the 'coincidence factor', f_{coinc}. This factor represents the ratio between the system peak demand for a group of dwellings over time period Δt, to the sum of the individual dwelling peaks over the same period. The calculation of f_{coinc} is shown in Equation 4:

$$f_{coinc} = \frac{Q_{peak,system}}{\sum_i Q_{peak,i}} \tag{4}$$

$Q_{peak,system}$ [kW] is the maximum coincidental total demand for a group of customers during period Δt, and $Q_{peak,i}$ [kW] is the peak load for customer i over the same time period (Gönen 1986). Like f_{load}, f_{coinc} varies between zero and one. When $f_{coinc} \approx 1$, all customers are achieve peak demand at the same time. Short (2003) stated that f_{coinc} is often much less than one, since customers typically do not realize peak demand at the same time.

Comparison of f_{coinc} between the measured and modelled is an important metric to consider for applicability of the AL model for estimating demands for DG system design. Large values of f_{coinc} in the model would over-estimate the peak demand of the aggregated load, leading to over-sizing of generation equipment. Conversely, under-estimation of f_{coinc} by the AL model would lead to under-estimation of system peak demands and equipment size.

Two 'system' AL demand profiles were constructed from concurrently measured AL demands collected by Saldanha and Beausoleil-Morrison (2012) and Johnson and Beausoleil-Morrison (2017), identified as 'group 1' and 'group 2', respectively. Each group of AL demand profiles were paired with their corresponding modelled profiles, described in Section 3.2, yielding eleven measured and eleven modelled profiles per group. To account for weather and social factors, measured system AL demands were developed by aggregating demands over coincident measurement periods. The data from Saldanha and Beausoleil-Morrison (2012) and Johnson and Beausoleil-Morrison (2017) contained 300 and 333 days of concurrent demand measurement, respectively. Daily coincident factors were determined for each concurrently measured day in each group. For the modelled profiles, all 356 days of demand were used in the aggregation.

The individual and aggregated AL demands were used to determine the daily coincidence factors, $f_{coinc,daily}$. The distributions of $f_{coinc,daily}$ are plotted in Figure 8.
Comparing measured to modelled in each group for each day type, Figure 8 shows that the model tends to under-predict $f_{coinc,daily}$ compared to the measured values. The modelled mean $f_{coinc,daily}$ values were between 1.3% to 9.1% smaller than the corresponding measured $f_{coinc,daily}$ values in the same group. Two-sample t-tests were used to examine the significance of these differences. For weekdays, the differences of the means in groups 1 and 2 were significant, with p-values of 2.88e^{-6} and 4.46e^{-9}, respectively. The mean weekend $f_{coinc,daily}$ values were also found to be different for group 1, with a p-value of 4.00e^{-6}. For group 2 however, the means were found to be similar, with a p-value of 0.531.

The lower $f_{coinc,daily}$ values produced by the model suggest that there is greater diversity in

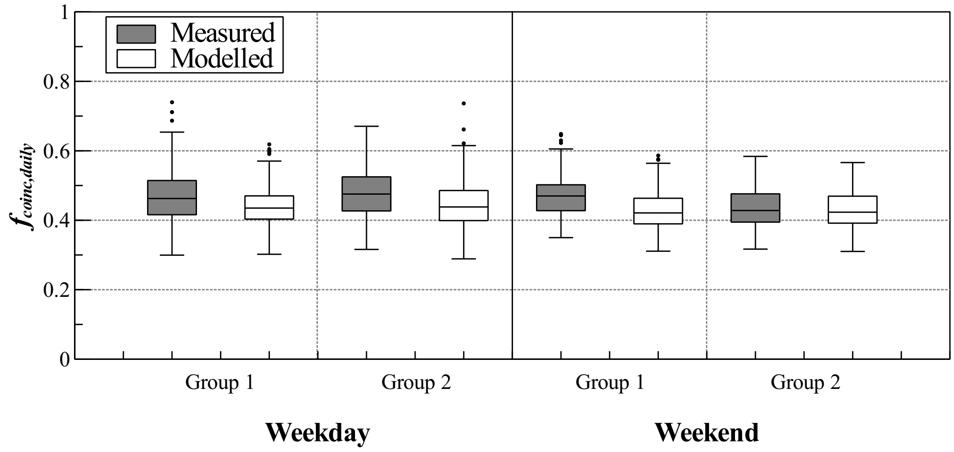


Figure 8. Weekday and weekend daily coincidence factors

peak AL demand occurrence amongst the dwellings compared to the measured profiles. In the absence of detailed information on occupancy and plug-load demand in the measured data, it is difficult to discern the reason for this difference. One possible explanation is the exclusion of a social factor in the CREST model. Paatero and Lund (2006) had previously defined a social factor in their residential electrical load consumption model to account for groups of dwellings influenced simultaneously by large events such as climate and television. The CREST model partially accounts for climate by using solar irradiance as input to the lighting module, but not other factors such as temperature and precipitation.

The variation of $f_{coinc,daily}$ between measured and modelled in each group was also compared using the Brown-Forsythe test. Variance was found to be similar between measured and modelled, with the exception of weekday $f_{coinc,daily}$ in group 1. The p-value for that group was determined to be in the order of 10^{-4}. All other day types and groups have p-values between 0.550 and 0.657.

4. Impact of baseload implementation

The current implementation of the CREST model added an unallocated constant baseload demand to each AL demand profile generated. The magnitude of the baseload demand was determine stochastically for each profile generated, using a Gaussian distribution defined by mean and standard deviation values provided by the user. To examine the impact of this added baseload, the baseload value was set to zero and the appliance module in the CREST model was re-calibrated using the procedure described previously in Section 3.1. Inputs for standby power demand of appliances were still included in the model.

The $C_{appl,calibrate}$ values for SD and DR dwellings were determined to be 4.35 and 2.11, respectively. When the baseload was included in the CREST model, these values were 2.36 and 0.50, respectively. $C_{appl,calibrate}$ is a scalar which is directly multiplied to the $N_{i,cycles}$ for each appliance i. For the set without a baseload, $N_{i,cycles}$ had to be increased to achieve the same user specified nominal annual AL consumption target. The lighting calibration scalar, $C_{light,calibrate}$, was not recalibrated.

To compare the two calibrated CREST models, 330 available CSDDRD Ottawa, ON records were randomly selected. The ratio of SD to DR dwellings was 4:7 to reflect the ratio of dwelling types in the measured data. Annual AL demand profiles were generated for each of these profiles using both calibrated CREST models. The annual mean daily weekday demand profile were determined for both sets, and are plotted in Figure 9. The profile for the measured data is also included for reference.

It can be seen in Figure 9 that the inclusion of the baseload demand improves agreement with

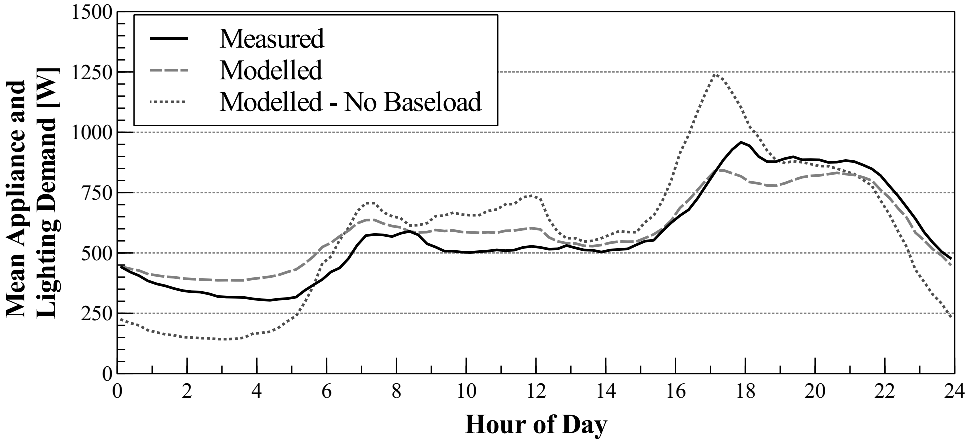


Figure 9. Comparison of annual mean daily weekday demand profiles with and without baseload input

measured data in terms of mean night-time demand. Additionally, the inclusion of the constant baseload also reduced the baseload to peak demand variation. To quantify the differences between the models, the annual baseload and peak demands were determined for each profile in both sets. The mean baseload demand was 292 and 43 W for the sets with and without the stochastic baseload input, respectively. The mean annual peak demands were found to be 1.42 and 2.64 kW, respectively. Both baseload and peak demand differences were found to be significant using a two-sample t-test. For reference, the mean annual baseload and peak demands of the measured data was 133 W and 1.7 kW, respectively.

The variation of the annual baseload and peak demands were also compared between modelled sets. The standard deviation of the annual baseload with and without the stochastic baseload input was determined to be 76 and 17 W, respectively. For annual peak demand, the standard deviation was 825 and 625 W, respectively. The Brown-Forsythe test also determined that the differences of variance were significant for both baseload and peak demands. For reference, the standard deviation of the annual baseload and peak demands of the measured data was 100 and 987 W, respectively.

Caution should be taken when comparing the absolute values of measured and modelled baseloads, since the mean and variation inputs of the stochastic baseload input included here were derived from the measured data. What this section highlights however, is that in the absence of the stochastic baseload input the model tends to under-predict the mean and variation of baseload demands. Additionally the absence of the stochastic baseload input also increased the mean annual peak demand and reduced the variation of annual peak demand among simulated profiles.

5. Conclusions

The current work adapted the CREST model previously developed by Richardson et al. (2010) to simulate the appliance and lighting (AL) demands of Canadian single-detached and double/row dwellings. Relevant Canadian data was collected and integrated into the CREST model, and an in-sample validation was performed using 22 measured annual AL demand profiles. The purpose of this validation was to examine if the nominal AL demand characteristics were similar between measured and modelled, as well as examine if the variation of AL demand characteristics within and between dwellings were also realistic. Overall the results show that the CREST model has the potential to generate the temporal and inter-dwelling diversity of AL demands seen in the practice. Such capabilities are useful for analysing residential community-scale energy demands and studying the design and feasibility of retrofitted distributed generation systems.

The results of the in-sample validation indicate that the adapted CREST model is capable of largely capturing the mean daily AL demands observed in the measured data. The variation of the daily AL demand was also found to be similar to measured for weekday periods, however the model under-estimated midday demand and variation compared to the measured data. The model was found to be follow similar seasonal variation of daily AL energy consumption as the measured data, however the variation in seasonal evening demand was found to be under-estimated in the model. The current CREST model only incorporates seasonal variation through changes in lighting use.

Two additional power demand characteristics were used to compare the measured and modelled AL demand characteristics: daily load and coincidence factors. Weekday and weekend load factors were considered separately. The model was shown to largely reproduce the daily variation of both factors, however the model tended to under-predict the mean daily coincidence factors. This indicates that there is generally larger variation in peak occurrence in the modelled AL demand profiles compared to the measured data. The good agreement of the mean and variation of the daily load factors indicates the model properly captures the typical daily fluctuation in AL demand, as well as the periods of high and low daily AL demand fluctuation seen in the measured data.

A stochastically determined AL baseload demand was also developed and implemented as part of this study. The inclusion of an unallocated baseload demand was shown to improve model annual baseload demand estimation, as well as annual peak demand estimation. In the absence of the stochastic baseload input, the model was found to under-estimate baseload demand as well as over-estimate annual peak demand.

Finally, the measured annual AL demand profiles were used to validate the aggregation of day types into weekdays and weekends. Using balanced one-way ANOVA and Brown-Forsythe tests, the mean and variation of daily AL demands was found to be statistically similar within weekdays and weekends. This finding added validity to the aggregation of day types as weekdays and weekends.

It is important to note that the sample of measured dwellings used in this study is relatively small, and is not necessarily representative of the larger Canadian residential stock. The results presented here give a strong indication that the CREST model can produce realistic and diverse AL demand profiles. Further work and validation should be carried out as data becomes available. Recommendations are provided in the following section.

6. Recommendations and Future Work

A major challenge for the current work was the lack of measured data available. Electrical consumption data is typically reported as the aggregate dwelling demand, which includes the dwelling HVAC and domestic hot water preparation systems. In order to validate and calibrate the appliance and lighting modelling capabilities of the CREST model, additional profiles similar to the non-HVAC profiles collected by Saldanha and Beausoleil-Morrison (2012) and Johnson and Beausoleil-Morrison (2017) are required. The 22 profiles from Saldanha and Beausoleil-Morrison (2012) and Johnson and Beausoleil-Morrison (2017) were used in the current work, however it would be irresponsible to claim that they are representative of the entire Canadian housing stock. A larger sample size, over a broader geographic area would be ideal. Additionally, new samples should be collected over a coincident period to permit valid aggregation of the demands.

Richardson et al. (2010) had previously noted that the CREST model under-estimated the seasonal variation of AL demands. In the current work, the model was found to follow the seasonal variation in mean daily AL energy demand. When the seasonal differences in the mean daily demand profile was considered in Figure 4 however, it was found that winter evening demands were higher for weekends compared to summer. Lighting and entertainment appliances (i.e. televisions) are primarily used during this period, along with cooking. Seasonal variation of appliance usage may be integrated into the CREST model by varying the appliance $N_{i,cycles}$ variable at each timestep. Flett and Kelly (2017) varied kettle, microwave, and dryer usage sinusoidally in their UK residential energy demand model. Sets of activity profiles could also be constructed for different months and seasons, however Fischer, Härtl, and Wille-Haussmann (2015) had previously analyzed TOU data from Germany, and found that the number of daily appliance starts varied seasonally, not the time of occurrence. Currently, there is little information on the seasonal variation of appliances in Canada. The SHEU 2011 report (NRCan 2014) does provide some information on seasonal dryer variation. Seasonal usage data for cooking and entertainment activities, largely performed in the evening, would likely improve model performance.

The current work used several sources to estimate appliance power demand, ON duration, and usage. The only plug-load data used in the current work however, was to define the cycle demand profile for washers, dryers, and dishwashers. Plug-load appliance data would be beneficial for determining cycle demand characteristics and durations, seasonal variation, and time of use. Additionally, all appliances modelled in the CREST use nominal power ratings supplied by the user. When each appliance is modelled, the actual ON power demand is determined stochastically using a Gaussian distribution with a mean equal to the nominal ON power demand and standard deviation assumed to be 10% of the nominal demand. The actual variation of nominal power demand for several of the appliances listed in Table A1 are unknown. Future work would examine if model performance would improve with improved estimates in the variation of power demand within each appliance type.

Lastly, it was noted in Section 3.3.4 that the CREST model tended to under-predict the daily coincidence factors for the groups of demands considered. It would be interesting to consider methods of implementing a social factor similar to what has been suggested by Paatero and Lund (2006). Currently, the CREST model uses solar irradiance as a common boundary condition to all modelled dwellings. Consideration of social factor in the CREST model could potentially increase the values of the daily coincidence factors and improve agreement with the measured data.

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Appendix A. Estimated appliance inputs

Table A1. Appliance inputs

Appliance	Mean ON Power [W]	Standby [W]	Cycle length [min]	Cycles per year	Activity
Microwave	1433 [3]	3 [3]	4 [5]	365 [5]	cooking
Small range 1	1200 [4]	0	19 [7]	12 [7]	cooking
Large range 1	2400 [4]	0	19 [7]	37 [7]	cooking
Small range 2	1200 [4]	0	19 [7]	188 [7]	cooking
Large range 2	2400 [4]	0	19 [7]	581 [5]	cooking
Dishwasher	500 [4]	0 [8]	124 [6]	181 [5]	cooking
Clothes Washer	500 [4]	1 [8]	40 [6]	211 [5]	laundry
Clothes Dryer	5000 [4]	1 [8]	75 [6]	177 [5]	laundry
Regular TV	80 [4]	4 [2]	168 [1]	401 [1]	tv
LED TV	119 [4]	4 [2]	168 [1]	401 [1]	tv
Plasma TV	219 [4]	4 [2]	168 [1]	401 [1]	tv
DLP TV	175 [9]	4 [2]	168 [1]	401 [1]	tv
LCD TV	150 [9]	4 [2]	168 [1]	401 [1]	tv
Projector	225 [9]	4 [2]	168 [1]	401 [1]	tv
TV receiver	30 [3]	17 [3]	168 [1]	401 [1]	tv
DVD/VCR	14 [3]	5 [3]	131 [1]	24 [1]	tv
Central vacuum	1600 [4]	0	130 [1]	97 [1]	house_clean
Spa tub	3040 [2]	0	45 [1]	52	wash_dress
PC	106 [3]	5 [3]	71 [1]	838 [1]	PC
Printer	9 [2]	2 [2]	7 [2]	730 [2]	PC
CD player	10 [3]	5 [3]	94 [1]	2 [1]	active_occ
Stereo	14 [3]	8 [3]	74 [1]	4 [1]	active_occ
Iron	1350 [2]	0 [2]	35 [8]	30 [8]	ironing
Vacuum	1080 [2]	0 [2]	130 [1]	97 [1]	house_clean
Kettle	1500 [4]	0	10 [4]	365 [4]	active_occ
Hair dryer	1500 [2]	0 [2]	5	365	wash_dress
Game console	27 [3]	1 [3]	140 [1]	30 [1]	tv
Sauna	11000	0	15	52	active_occ
Aquarium	39 [2]	39 [2]	N/A	N/A	other
Water cooler	160 [4]	160 [4]	N/A	N/A	other

[1] (Statistics Canada 2010)

[2] (DOE 2011)

[3] (LBNL 2017)

[4] (Hydro One Networks Inc. 2017)

[5] (NRCan 2014)

[6] (Saldanha and Beausoleil-Morrison 2012; Johnson and Beausoleil-Morrison 2017)

[7] (Klug, Lobscheid, and Singer 2011)

[8] (Richardson et al. 2010)

[9] (DOE 2017)