Energy and Buildings 43 (2011) 326–337

Contents lists available at ScienceDirect

Energy and Buildings

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

Occupant related household energy consumption in Canada: Estimation using a bottom-up neural-network technique

Lukas G. Swan [a,*], V. Ismet Ugursal [a], Ian Beausoleil-Morrison [b]

[a] Department of Mechanical Engineering, Dalhousie University, 1360 Barrington Street, Halifax, Nova Scotia B3J 1Z1, Canada
[b] Department of Mechanical and Aerospace Engineering, Carleton University, 1125 Colonel By Drive, Ottawa, Ontario K1S 5B6, Canada

ARTICLE INFO

Article history:
Received 12 January 2010
Received in revised form
14 September 2010
Accepted 25 September 2010

Keywords:
Residential energy
Residential model
Occupant energy
Neural network
Household energy
Domestic hot water
National energy model

ABSTRACT

A national model of residential energy consumption requires consideration of the following end-uses: space heating, space cooling, appliances and lighting (AL), and domestic hot water (DHW). The space heating and space cooling end-use energy consumption is strongly affected by the climatic conditions and the house thermal envelope. In contrast, both AL and DHW energy consumption are primarily a function of occupant behaviour, appliance ownership, demographic conditions, and occupancy rate. Because of these characteristics, a bottom-up statistical model is a candidate for estimating AL and DHW energy consumption. This article presents the detailed methodology and results of the application of a previously developed set of neural network models, as the statistical method of the Canadian Hybrid Residential End-Use Energy and Greenhouse Gas Emissions Model (CHREM). The CHREM estimates the national AL and DHW secondary energy consumption of Canadian single-detached and double/row houses to be 248 PJ and 201 PJ, respectively. The energy consumption values translate to per household values of 27.8 GJ and 22.5 GJ, and per capita values of 9.0 GJ and 7.3 GJ, respectively.

1. Introduction

In most countries, energy use of the residential sector accounts for 16–50% of that consumed by all sectors nationally, and averages approximately 30% worldwide [1]. This significant consumption level warrants a detailed understanding of the residential sector's consumption characteristics to prepare for and help guide a desired reduction in energy consumption. The residential sector uses secondary energy. Secondary energy is that received in suitable form for use by the consuming systems to support the living standards of occupants (e.g. natural gas, electricity). The major end-uses of secondary energy within a dwelling are:

- Space heating and space cooling energy consumption is that required to support heat transfer across the building envelope due to conduction and radiation, as well as air infiltration/ventilation, and internal heat gains in an effort to maintain the living space at a comfortable temperature and air quality.
- Domestic hot water (DHW) energy consumption is that required to heat water to a comfortable or appropriate temperature for occupant and appliance use.
- Appliances and lighting (AL) energy operates common appliances (e.g. refrigerator, coffee maker) and for the provision of adequate lighting.

There are relationships between these end-uses. For example, AL energy consumption generates heat that may offset space heating or increase space cooling energy requirements. Additionally, the relative magnitude of each end-use varies dramatically with climate, mechanical systems and technologies, building thermal characteristics, and occupant use. Each end-use presents unique opportunities for reduction of energy consumption.

An appropriate method to examine these end-uses and energy reduction opportunities is through the use of energy models. A recent review of residential sector energy consumption models by Swan and Ugursal determined that each unique *approach* has positive and negative attributes [2]. Top-down approach models such as the USA National Energy Modeling System [3] heavily weigh previous years experience and may be used to forecast residential energy supply requirements due to macro changes such as economic conditions or seasonal climatic variance. Bottom-up approach models such as the Scottish Domestic Energy Model [4] and the Canadian Residential End-use Energy Model [5] estimate the energy consumption of detailed representative house descriptions and scale these values up to a national context. Because bottom-up models use detailed house descriptions, they are superior in handling technological advancements

* Corresponding author. Tel.: +1 902 494 4643; fax: +1 902 423 6711.
E-mail address: Lukas.Swan@Dal.ca (L.G. Swan).

0378-7788/$ – see front matter © 2010 Elsevier B.V. All rights reserved.
doi:10.1016/j.enbuild.2010.09.021

such as those targeted towards reducing energy consumption.

Bottom-up models that are representative of the national housing stock may be used to assess the potential impacts of adopting renewable and alternative energy technologies within the residential sector. Such models may be used to develop strategies, such as incentive programs to promote technologies, by quantifying the potential energy and greenhouse gas emissions savings of a technology. As with the modeling approaches discussed above (i.e. top-down or bottom-up), there are different bottom-up *methods*, each with particular strengths.

It is appropriate to select a modeling method based on the particular end-use under investigation. Steemers and Yun succinctly showed that climatic conditions and the thermal envelope dominate the magnitude of space heating, enabling models based on the *engineering* method of thermodynamic and heat transfer principles to adequately represent the space heating energy consumption [6]. They also showed that climatic conditions and the occupants' use of space cooling dominate its energy consumption, while the thermal envelope is only weakly related. Because the subjective occupant participation in space cooling energy consumption has greater influence than the thermal envelope, the engineering method is not considered optimal for this end-use. However, the engineering method may still be utilized to model space cooling for the purpose of energy consumption investigation because of the following characteristics:

- Space cooling and renewable energy technologies are primarily dependent upon climatic conditions.
- Renewable energy technologies such as photovoltaics may be used to meet the space cooling end-use energy consumption.
- The engineering method is capable of modeling and integrating the energy generation of variable renewable energy technologies with the energy use of space cooling.

In contrast with the climate dominated space heating and space cooling, both the AL and DHW energy consumption are primarily a function of occupant behaviour, appliance ownership, demographic conditions, and occupancy rate. Because of these characteristics, a model based on the *statistical* method is a candidate for estimating AL and DHW energy consumption. A variety of statistical methods have been used for modeling residential energy consumption, such as: conditional demand analysis [e.g. 7], neural networks [e.g. 8], and genetic algorithms [e.g. 9].

For Canada, the Canadian Hybrid Residential End-use Energy and Greenhouse Gas Emissions Model (CHREM), presently being developed by Swan et al. [10], takes advantage of these two bottom-up methods; hence the word *hybrid*. The CHREM employs an artificial neural network (NN) as its statistical method and uses it to estimate the AL and DHW energy consumption. The results of the CHREM statistical method are then integrated with an engineering method that estimates the space heating and space cooling energy consumption using the numerical building simulation software ESP-r [11,12]. By using this hybrid of methods (engineering and statistical models), the CHREM takes advantage of the strengths of both bottom-up methods.

The CHREM relies on a set of nearly 17,000 unique house descriptions of the Canadian Single-Detached and Double/Row housing Database (CSDDRD). The CSDDRD was developed by Swan et al. to provide a high degree of representation of the Canadian housing stock by encompassing the variety of thermal envelope and mechanical systems as well as the regional distinctions [13]. The data which forms the CSDDRD originates from the EnerGuide for Houses Program which conducted detailed energy audits of over 165,000 dwellings and is described by Blais et al. [14].

The CSDDRD contains explicit descriptions of each house's thermal envelope and mechanical systems, which allows for a representative house model to be generated and simulated in the CHREM engineering method, for the estimation of space heating and space cooling energy consumption. However, the CSDDRD information comes from home energy audits that did not assess common household appliances (e.g. refrigerator size, number of light bulbs) or demographics. Such data are required to estimate the AL and DHW energy consumption using the CHREM statistical method. The provision of such data is one of the important topics addressed in this article.

This article presents the detailed implementation methodology and the results of the application of a previously developed set of NN models, as the CHREM statistical method. The methodology of providing input data and integrating the AL and DHW energy consumption results with the CHREM engineering method for the estimation of the space heating and space cooling energy consumption is presented in the following section. The AL and DHW energy consumption estimations and their comparison with existing models and estimations are presented in Section 3.

2. Methodology

The hybrid modeling approach of the CHREM relies on a NN for the estimation of AL and DHW energy consumption. A NN is a large number of highly interconnected processing elements tied together with weighted connections. Because of this, a NN is capable of nonlinear processing and can be used to find internal representations within raw data. A NN is calibrated much like other regression models, by providing a set of input and expected output data. A variety of iterative methods are available to modify the weighted connection values in an attempt to reduce the prediction error. An example of a simple NN is shown in Fig. 1. The example NN has three layers: the input layer with three scaled inputs, the hidden layer with two nodes, and an output layer. Raw inputs are scaled to provide data to each of the internal hidden layer nodes, where an array of multipliers is applied and a bias is added to the accumulated values. A similar process is evaluated to pass the hidden node information to the output layer, after which it is scaled to the appropriate output units.

A comprehensive review of the utilization of the NN method for modeling residential sector energy consumption has been discussed and compared to other methods by Aydinalp et al. [15,16]. The NN method was found to have superior prediction capability for the AL and DHW end-uses, primarily due to the ability of discerning occupancy use trends which have no relevance to engineering analysis. Because of this superiority, the NN method was chosen for use as the statistical method of the CHREM for the estimation of annual AL and DHW energy consumption. The following sections describe the NN implementation within the CHREM.

2.1. AL and DHW artificial neural network models

Two NN models that estimate annual electrical energy consumption due to AL and space cooling, and annual energy consumption due to DHW have been developed and demonstrated by Aydinalp et al. [8,17]. These models were calibrated for the Canadian housing stock using data from the Survey of Household Energy Use 1993 (SHEU), a national housing stock assessment [18]. Key to this dataset is household billing information for a variety of energy sources. By exploiting the differences among houses due to energy sources, the consumption of a particular end-use was identified. For example, houses that use natural gas as the energy source for both space heating and DHW purposes may be used to calibrate the AL and space cooling NN on the basis that the entire electricity con-

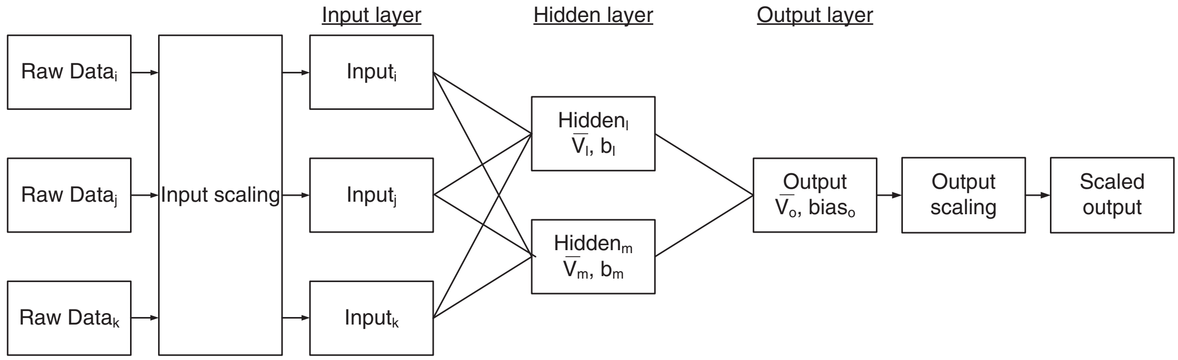

Fig. 1. Simplified NN (architecture 3:2:1) with three inputs, two internal processing elements with coefficient arrays "$\bar{V}$" and bias "b", and one output processing element.

sumption could be attributed to these end-uses. It should be noted that in such a case, any fans or pumps associated with the space heating or DHW systems would have their electrical energy consumption accounted for by the AL and space cooling NN. A similar calibration process was used for the DHW NN with the exception that for cases where the DHW was supplied by electricity, the AL and space cooling NN is used first to determine the remaining electricity consumption that is attributable to the DHW.

The SHEU 1993 dataset identified presence and use of a wide variety of common appliances (e.g. refrigerator) as well as household demographics. The values were used as inputs to the NN models. By conducting comparative testing, Aydinalp et al. selected the NN configuration that produced the most accurate estimate for each end-use [8,17]. The selected configurations are shown in Table 1. Because the CHREM estimates the space cooling energy consumption using the engineering method, this aspect of the AL and space cooling NN was not utilized (henceforth it is called the AL NN).

Once calibrated, a NN model is a set of mathematical functions described by the architectural configuration, scaling, vectors of weights and bias, and activation functions. Using these values as defined by Aydinalp [19] the NNs were recreated in the CHREM, requiring only a set of input data upon which to calculate. Because there is no iteration and only a limited set of mathematical functions, the calculation time to execute both the AL and DHW NN models for the 17,000 unique houses of the CHREM requires less than 1 h with a common computer.

2.2. NN input data

The NN models require suitable input data in order to perform the calculations and arrive at annual energy consumption. There is distinct input data for the AL and the DHW networks, as well as common data that affects both consumption types. For example, both a clothes washer and dishwasher use electricity and hot water. Because the AL and DHW energy consumption is heavily affected by occupant behaviour, many of the required inputs are related to the household demographics. A listing of the input data for the AL and DHW NN models is shown in Table 2. Aydinalp [19] selected the NN inputs on the basis of expected effect and data availability within the SHEU 1993 dataset.

The lack of common appliance and demographic data in the CSDDRD, the source dataset for the CHREM, necessitates the provision and manipulation of suitable data to populate these NN inputs for each house. Such input data can be populated using regional distributions obtained from housing surveys or census information. A listing of the data sources for the NN models (both explicit CSDDRD data and survey/census distributions) is provided in Table 2, and a description of the data sources for explicit and distribution information follows.

2.2.1. Explicit input information

The CSDDRD includes explicit data that is utilized for certain NN inputs as shown in Table 2. These are primarily related to mechanical systems of the house (e.g. heat-recovery ventilation system) and the thermal envelope (e.g. heated floor area). DHW system energy factor was based upon the DHW energy source present in the house and a lookup table used to calibrate the NN, as shown in Table 3. These fixed annual energy factors are equal to the ratio of the DHW delivered thermal output to the higher heating value of the energy source, which accounts for the system flue and skin losses. The values shown in Table 3 are representative of DHW systems found in the Canadian housing stock.

The CSDDRD includes postal code data and the city and province name for each house. This is used as a location identifier for census and climatic data to determine population density (e.g. rural, urban) and climatic conditions such as soil temperature and heating/cooling degree days (HDD/CDD).

The population density was found using the Canadian Postal Code Conversion File [20] which relies on the "Population distribution of census subdivision areas" of the 2006 Canadian census [21]. This database contains a cross reference of all six-digit postal codes from which an urban/rural indicator may be determined. This variable was mapped as indicated in Table 4 to determine the population density at each house.

Climatic data is published by Environment Canada [22]. These data represent average or "normal" climatic conditions for a particular location, as determined from several decades of actual data. A cross reference that mapped all of the weather cities present in the CSDDRD (65 different locations) to the most representative weather station (44 different locations) based on location (latitude and longitude) and heating degree days was developed. Using the city name associated with each house, the most representative

Table 1
Characteristics of the AL and space cooling, and DHW NN models [8,17].

NN type	Architectural configuration	Scaling	Activation function	
			Hidden nodes	Output node
AL and space cooling	55:9:9:9:1	−0.5 to +0.5	Logistic	Identity
DHW	18:29:1	+0.1 to +0.9	Logistic	Logistic

Table 2
Inputs to the DHW and AL neural network models.

Model	Input data source			
	CSDDRD	SHEU 1993	SHEU 2003	Census 2006
Common inputs to both the DHW and AL models	Dwelling type		Dishwasher use	No. of adults
	Population density		Clothes washer use	No. of children
			Ownership	
			Income	
DHW specific inputs	System energy factor	Storage tank age	Storage tank size	
	Soil temperature		Pipe insulation	
			Insulating blanket	
			No. of low flow shower heads	
			No. of tap aerators	
AL specific inputs	Heated area	Supplementary heat	Main refrigerator size	Employment ratio
	Furnace fan	Electric blanket	Secondary refrigerator size	
	Boiler pump	Water bed	Stove	
	Central air exchanger	Humidifier	Main freezer size	
	Heat recovery ventilator	Dehumidifier	Secondary freezer size	
	No. of bathroom exhaust fans	Fish tank	Microwave	
	Heating degree days	Central air filter	Color TV	
	Cooling degree days	Central humidifier	VCR	
		Central dehumidifier	CD player	
		Central vacuum	No. of halogen bulbs	
		Sump pump	No. of fluorescent bulbs	
		Water softener	No. of incandescent bulbs	
		Car block heater	Water cooler	
		Car warmer	Ceiling fan	
		Sauna	Clothes dryer	
		Jacuzzi	Stereo	
			Computer	

HDD and CDD (18 °C base temperature), and annual average soil temperature at 1.5 m depth were selected.

2.2.2. Distribution input information

The majority of the NN inputs relate to appliance presence and use within a dwelling. As the CSDDRD has limited appliance and demographic information, many of these inputs must be populated using SHEU information. The most recent SHEU 2003 is available only as distributions based on house type and region [23]. The two house types under consideration in the CHREM are:

- Single-detached (SD) houses are a free-standing single-family home.
- Double/row (DR) houses are single-family homes which are adjoined to other houses on either one or two sides.

These house types account for 80% of the Canadian housing stock, the balance being apartments and mobile homes [23]. There are five distinct Canadian regions with populations greater than one million people:

- Atlantic (AT) consisting of provinces Newfoundland and Labrador, Nova Scotia, Prince Edward Island, and New Brunswick
- Quebec (QC)
- Ontario (ON)
- Prairies (PR) consisting of provinces Manitoba, Saskatchewan, and Alberta
- British Columbia (BC)

Table 3
Mapping of DHW equipment type to system energy factor [19].

DHW energy source	DHW system energy factor (%)
Electricity	82.4
Natural gas or propane	55.4
Oil	53.0
Wood	30.0

Table 4
Mapping of the Postal Code Conversion File to the NN input.

Urban/rural indicator	Mapped NN population density input
Rural area	Rural
Urban core	Urban
Urban fringe	Suburban
Urban areas outside census areas	Suburban
Secondary urban core	Urban
Dissemination areas only	Rural

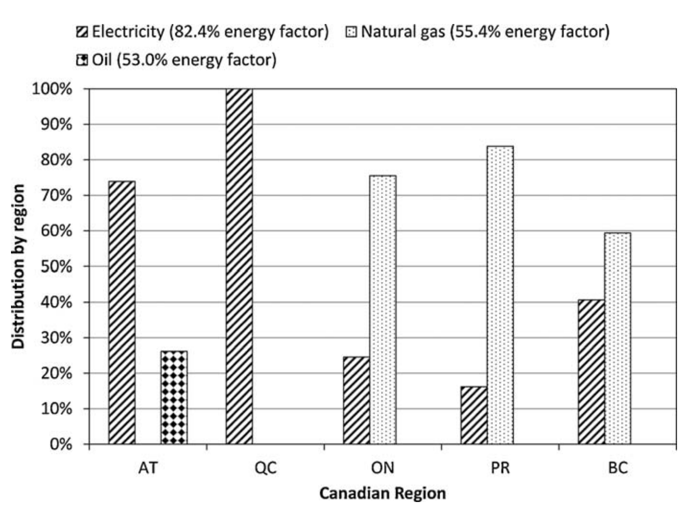

Fig. 2. Canadian regional DHW energy source distributions for the SD and DR house types [23].

Table 5
Mapping of regional household structure to number of adults, children, and employment ratio.

Household structure	Adults	Children	Possible employment ratio fields
10–13	1	0–3	0.00, 1.00
20–23	2	0–3	0.00, 0.50, 1.00
30–33	3	0–3	0.00, 0.33, 0.66, 1.00
40	4	0	0.00, 0.25, 0.50, 0.75, 1.00

To illustrate this regional distinction, Fig. 2 shows the regional distribution of DHW energy sources[1] along with the representative system energy factors listed in Table 3. In addition to SHEU 2003 data, distributions based on the Canadian Census 2006 and 2001 were also used to populate the NN inputs [21,24].

Use of the distribution for populating the CSDDRD with appliance and demographic information relied on the finest resolution distribution available. The available distribution resolution levels in the order of descending resolution are:

1. Distribution specific to both the house type and region.
2. Distribution specific to the region for all house types.
3. Distribution specific to the house type on a national scale.
4. Distribution of the national housing stock.

Note that region specific distributions (#2) take precedence over house type specific distributions (#3). This is because appliance ownership and use, as well as demographics tend to be dependent upon cultural norms which are regionally distinct.

Once selected, the distribution was used to randomly populate the houses of the specific house type and region, in accordance with the distribution percentages. For example, if 50% of houses have one computer, 25% have two computers, and 25% have three computers, then the number of computers present in a household would be randomly applied to the houses in such a fashion as to maintain the distribution percentages.

The populating process was completed for each NN input which did not have an explicit value determined from the CSDDRD. There are certain NN inputs which are notably linked: number of adults, number of children, and employment ratio.

The number of adults and children was developed using a special keyed distribution of *household*. The relationship of adults to children within households is not explicitly stated by Census 2006, but can be determined for each region by a comparison of the tabulated data of "Household structure" and "Families" [21]. The fields of the household were set to a two digit integer where the first digit is number of adults and the second digit is number of children, as shown in Table 5. This household distribution maintains the adult to child household structure. If the number of adults and children were treated independently, this important household structure would be lost. Only after shuffling of the household array are the digits separated to determine the number of adults and children.

Employment ratio, the ratio of adults-employed to adults-in-the-household, requires the number of adults-in-the-household, because the possible employment ratio fields depend on this value, as shown in Table 5. Thus, employment ratio was completed as a separate populating process after the separation of the number of adults from the household field. Regional distributions of employment ratio were developed using the Computing in the Humanities and Social Sciences database tool [25] to examine the Census 2001 data [24].

[1] Although SHEU 2003 estimates approximately 7% of QC dwellings (all types) have natural gas powered DHW, the distribution of natural gas DHW by dwelling types for QC is considered unreliable [23].

2.3. NN model implementation and DHW conversion

Execution of the NN model involves a series of scaling and calculation routines that are completed using the scales, calibrated weights and biases, and activation functions developed by Aydinalp [19]. The process continues through each layer, arriving at an output value which is re-scaled to the desired units (e.g. GJ).

It is important to differentiate the clothes dryer energy consumption component as it is typically exhausted outside of the thermal zone and thus does not contribute as an internal gain within the conditioned zone. Additionally, both the clothes dryer and cook stove components may be powered by natural gas or electricity. Because of these unique attributes, the clothes dryer and cook stove must be differentiated from the other AL components which are powered solely by electricity. To accomplish this differentiation, a second round of houses was modeled that had the Clothes Dryer (loads/week) set to zero. By comparing the AL energy consumption of this variant with the original house, the impact due to the clothes dryer could be distinguished. Unfortunately, the cook stove could not be distinguished using the variant analysis method because a cook stove is present in nearly every house. This resulted in multicollinearity and inhibited the NN from properly identifying the cook stove contribution. The process of distinguishing the cook stove is described in Section 2.4.

The unit of energy consumption estimated by applying the AL or DHW network is annual GJ. This is suitable for analysis and the incorporation of the AL results into the CHREM engineering model. However, it is preferable to have the DHW consumption in terms of volume draw instead of energy consumption. This is because the DHW system technology can be modeled by the engineering model, allowing for the assessment of new technologies such as solar-thermal, increased thermal storage, or instantaneous water heaters.

The DHW energy consumption E_{DHW} (J) was converted to annual water draw volume V (m^3), using Eq. (1), by assuming a delivery temperature of 55 °C, and using the annual average soil temperature T_{G} (°C) and system energy factor value η (−) specified as inputs to the NN (see Table 3). The terms ρ (kg/m^3) and C_{p} (J/kg K) are the density and specific heat of water, respectively.

$$V = \frac{E_{\mathrm{DHW}}\eta}{\rho C_{\mathrm{p}}(55\,^{\circ}\mathrm{C} - T_{\mathrm{G}})} \tag{1}$$

2.4. AL and DHW load profiles

The estimates of annual AL energy consumption and DHW volume consumption must be translated onto representative sub-hourly load profiles for integration with the CHREM engineering method. This translation allows for the consumption profile to be compared to the energy production profile of, for example, renewable energy technologies such as photovoltaics or solar-thermal systems.

AL and DHW use profiles have been developed by a number of researchers. Yao and Steemers [26] developed AL and DHW energy load profiles for the UK residential sector. Armstrong et al. [27] developed AL electricity load profiles for the Canadian residential sector. Jordan and Vajen [28] developed DHW volume draw profiles for Europe. The profiles of Armstrong et al. [27] and Jordan and Vajen [28] were selected for the CHREM model as they are readily available on 5 min time step increments and are intended for energy simulation purposes. An example of these profiles is shown in Fig. 3. The profiles were developed and compiled for the International Energy Agency's Energy Conservation in Buildings and Community Systems Program [29].

There are two important considerations for implementing the AL and DHW consumption within the CHREM engineering method:

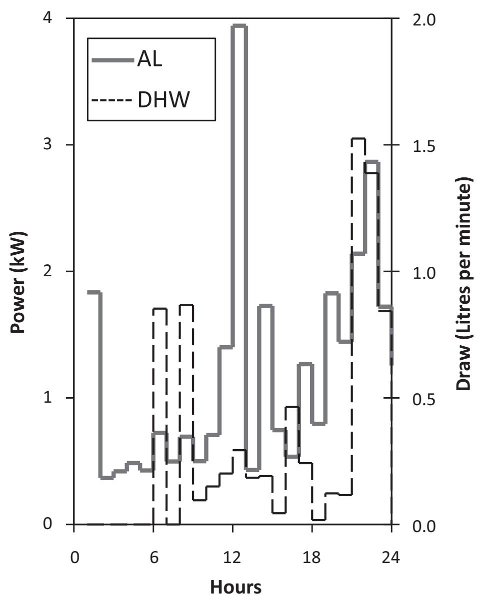

Fig. 3. Example AL and DHW hourly profile.

- Loads must be disaggregated by energy source
  - o The DHW load can be met by a variety of energy sources listed in Table 3.
  - o The AL loads are typically met using electricity, although nearly 10% of the CSDDRD has either a natural gas cook stove or clothes dryer. Therefore, the cook stove and clothes dryer AL components must have distinct profiles from the remaining AL components.
- Loads must be disaggregated according to their final destination of heat
  - o The energy used in the heating of DHW does not directly result in heating of the thermally conditioned zone as water is considered to immediately drain outside the dwelling. However, the CHREM engineering method does consider the heat loss to the thermal zone due to the storage tank and the piping.
  - o The energy used by the AL is considered to become a heat input to the thermal zone, with the exception of the clothes dryer which is exhausted outside.

Profiles are not only associated with a particular load, but also with the consumption level. For example, a clothes dryer may be approximated as a constant power device when running. In a high consumption household the frequency of use will be greater than in a low consumption household. Whereas, the lighting use in a high consumption household will have similar frequency of use to a low consumption household, but at a higher power level.

Three different AL and DHW usage profiles were available corresponding to *low*, *medium*, and *high* typical usage. In addition, the individual profiles for each AL component type were obtained so that the cook stove and clothes dryer could be differentiated for energy source and destination of heat purposes. Annual consumption levels are summarized in Table 6 and the contribution of individual AL components are shown in Fig. 4. *AL Other* refers to the

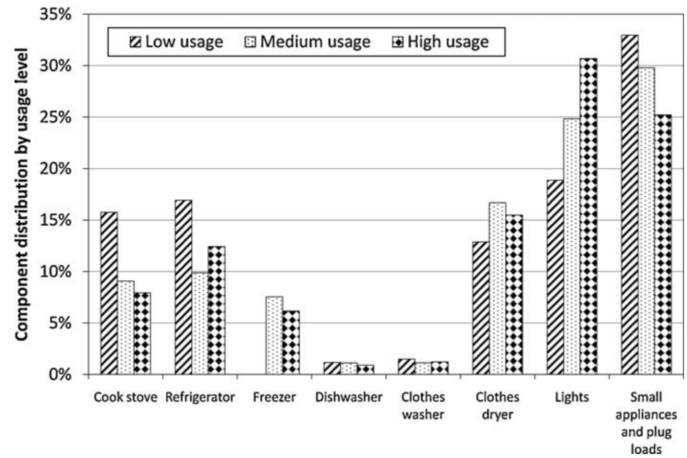

Fig. 4. AL component energy consumption distribution for three usage levels.

refrigerator, freezer, dishwasher, clothes washer, lights, and small appliances and plug loads.

2.5. Translation of NN annual energy and volume consumption values to time-step profiles

A translation of the NN estimates of annual AL energy and DHW volume consumption to appropriate time-step profiles (e.g. hourly) was completed to incorporate these end-uses with the CHREM engineering method. The selection of the most appropriate time-step profile was made by comparing the annual profile consumption to that estimated for the house by the NN. The profile that minimized the absolute difference in these annual consumption values was selected.

The profiles for the DHW, clothes dryer, and the cook stove and remaining AL components were selected individually. Because of the multicollinearity described in Section 2.3, the cook stove and remaining AL components were lumped together for purposes of choosing the most representative profile levels. The individual profile selection allows for a house to consume large volumes of DHW, and small amounts of energy for AL, or vice versa. This was especially important as it was found that the profiles developed by Armstrong et al. [27] estimate that the clothes dryer operates more frequently than predicted by SHEU 2003.

Although the selection of profiles minimized annual consumption differences between the profile and house, a multiplier was used to tailor the annual consumption of the profile to be identical to the house estimate. The multiplier, a ratio of the house consumption to the profile consumption, is used by the CHREM engineering method to linearly alter the time-step profile value. In the case where the cook stove is powered by natural gas, the multiplier was doubled to account for the appliance being half as efficient as an electric cook stove [30]. Natural gas clothes dryers were assumed to be as efficient as electric clothes dryers.

The sets of profiles and profile multipliers for each house of the CSDDRD are then passed to the CHREM engineering method. The engineering method conducts space heating and space cooling energy simulation taking into consideration the AL energy consumption and DHW volume draw. This integration allows the

Table 6
Annual consumption values of the three AL and DHW profile usage levels.

Use level	DHW (average L/day)	Cook stove (GJ/year)	Clothes dryer (GJ/year)	AL Other (GJ/year)
Low	100	2.7	2.2	12.2
Medium	200	2.7	4.9	21.8
High	300	3.7	7.2	35.7

Table 7
Annual AL and DHW energy consumption and DHW volume draw estimates of the CSDDRD.

Statistic	AL				DHW	
	Total (GJ)	Clothes dryer (GJ)	Cook stove (GJ)	Other (GJ)	Energy (GJ)	Volume (annual daily average L/day)
Minimum	10.1	0.0	1.7	7.5	10.4	98
Maximum	89.4	9.8	15.0	75.8	40.0	359
Average	27.9	1.3	3.0	23.4	22.6	208
Standard deviation	10.1	1.4	0.7	8.8	4.2	39

internal gains due to many of the AL component loads to offset space heating requirements or contribute to space cooling requirements. The energy source required to meet the load is known based on the house mechanical systems and these are appropriately aggregated by energy type in the simulation with the space heating and space cooling energy consumption.

3. Results and discussion

The results of the AL and DHW energy consumption, and DHW draw, are examined in the following subsections by house characteristics. They are then scaled up to obtain national values. A synopsis of the selected profiles and multipliers for their application into the CHREM engineering method is also provided.

3.1. Estimation of AL and DHW consumption of the CSDDRD

The CHREM statistical method was used to estimate the AL and DHW energy consumption for each of the 16,952 houses of the CSDDRD. In addition, the DHW values were converted from energy units to units of volume draw as described in Section 2.3. A description of the range of resulting values is listed in Table 7. These values account for natural gas powered cook stoves and clothes dryers. The range of total AL energy consumption is quite large, spanning nearly 80 GJ. The minimum AL clothes dryer value is zero, and represents houses that are either lacking a clothes dryer, or where the occupant does not use the clothes dryer.

DHW does not cover such a broad range and has an annual daily average of 208 L/day. This average value is 10–20% less than measured North American values summarized by Wiehagen and Sikora [31] and Aguilar et al. [32], and is due in part to their measurement focus on single-detached homes with dishwashers.

The distribution of AL and DHW energy consumption, and DHW volume draw, as a function of both house type and region is shown in Figs. 5 and 6. It is evident that on average single-detached (SD) households tend to consume more energy for both AL and DHW than double/row (DR) households. This is likely due to the increased floor area and appliance ownership of single-detached homes. Fig. 5 shows that the region of British Columbia (BC), the most westerly province in Canada, uses a higher amount of AL energy per household. This may be due to a milder climate, increased floor area size, or their higher than national average income [23].

Fig. 6 shows the DHW volume draw (6a) and energy consumption (6b) for comparison. The ranges of energy consumption were selected to mirror the draw ranges of a system that uses electricity and has an annual average soil temperature of 7.8 °C at 1.5 m depth. If all DHW systems in Canada were electric, the distributions would be similar between Fig. 6a and 6b. However, it can be seen that the energy consumption distributions tend towards higher ranges than the draw, indicating that less efficient DHW systems (e.g. natural gas, oil) are in use. This is the case, as natural gas and heating oil systems make up approximately 55% of the DHW systems in the CSDDRD, as shown in Fig. 2 where DHW system energy factor is listed in the legend. However, the high household DHW energy consumption of the prairies region (PR) shown in Fig. 6 cannot be wholly explained by the predominance of less efficient natural gas systems, as Fig. 2 shows they are also significant in Ontario (ON) and BC. Soil temperature may also affect DHW consumption. Fig. 7a shows that DHW energy consumption is influenced by climatic conditions (proxied by annual average soil temperature at 1.5 m depth). DHW energy consumption tends to be greater in areas with colder soil temperature (less than 8 °C). Fig. 7b indicates the relationship between region and soil temperature. The PR region has colder soil temperatures in comparison with the rest of Canada, averaging approximately 5 °C. This may partially explain the high DHW energy consumption of the PR region shown in Fig. 6b.

3.2. Scaling of the CSDDRD AL and DHW energy consumption to national values

An assessment of the national AL and DHW energy consumption was conducted by scaling the CSDDRD housing results to be representative of the respective house types and regions. Because of the selection algorithm used to develop the CSDDRD, each house type and region has an individual representation multiplier, although they are similar, which indicates adequate representation of each house type and region. These representation values are equal to the number of houses estimated by SHEU 2003 for the house type and region, divided by the corresponding number of houses in the CSDDRD. The representation level is shown in Table 8.

Using the AL and DHW results from the CSDDRD, and the representation values of Table 8, the regional and national energy consumption of these end-use types were calculated. The results are shown in Table 9. The CHREM estimates that 448.7 PJ of secondary energy is required for Canadian SD and DR house types to provide for the AL and DHW end-uses. The AL energy consumption is larger than the DHW, accounting for 55% of the consumed energy among these two end-uses. Electricity is the dominant energy source, providing for 73% of the overall AL and DHW energy

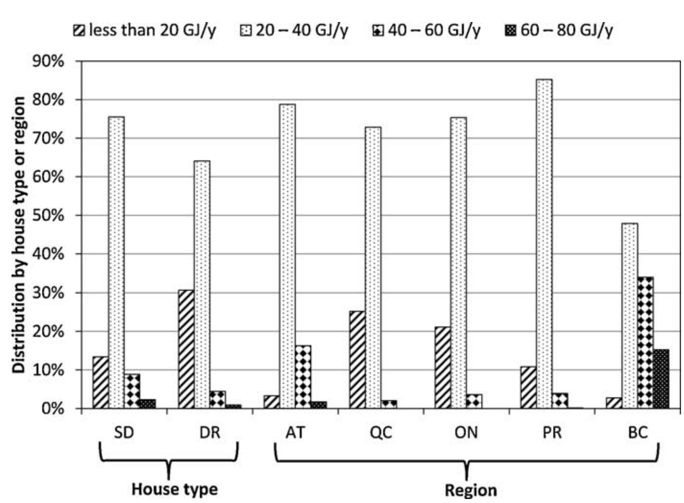

Fig. 5. Annual AL energy consumption estimates (GJ/year) obtained using the NN model – summarized by house type and region.

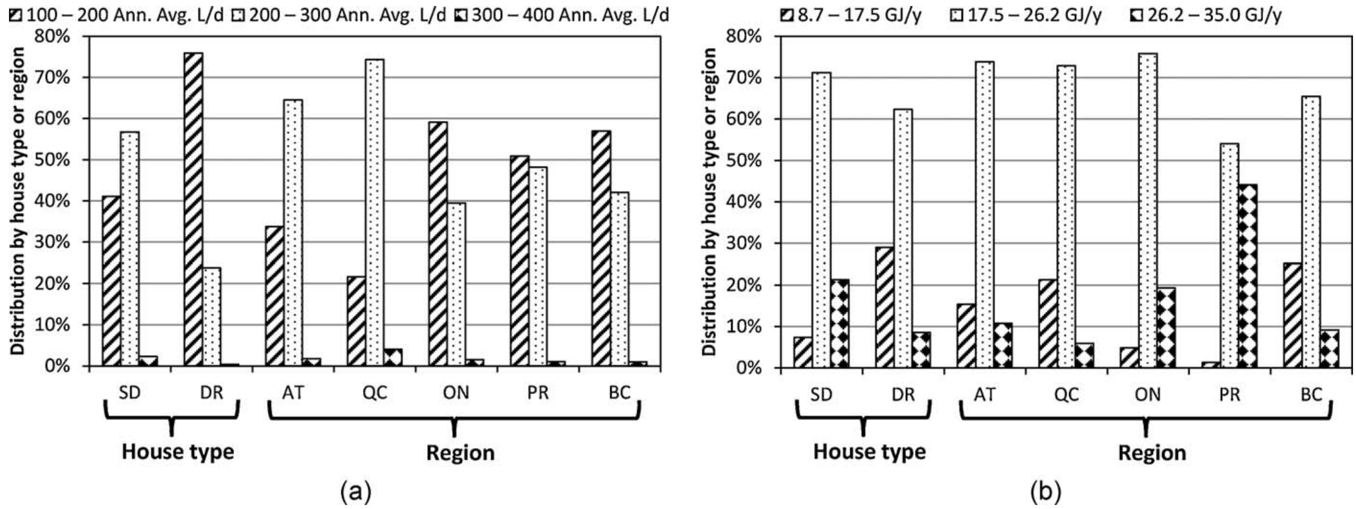

Fig. 6. DHW consumption estimates by house type and region, obtained using the NN model for (a) annual average daily DHW volume draw (L/day), and (b) annual energy consumption (GJ/year).

Table 8
Scaling representation from the CSDDRD houses to national values.

House type	Region	House count		CSDDRD/SHEU ratio (scaling representation)
		SHEU 2003	CSDDRD	
SD	AT	662,335	1271	521.1
	QC	1,513,497	2882	525.2
	ON	2,724,438	5404	504.2
	PR	1,381,219	2703	511.0
	BC	910,051	1770	514.2
DR	AT	94,150	137	687.2
	QC	469,193	798	588.0
	ON	707,777	1231	575.0
	PR	246,848	441	559.7
	BC	203,449	315	645.9

consumption. Heating oil is a minor energy source that is only applicable to the DHW end-use.

The contributions of each energy source to each end-use are shown in Table 10. It is evident that natural gas plays a minor role in supplying the AL end-use. This is because only the *AL stove* and *AL dryer* can be powered by natural gas and these are relatively minor components in comparison with the *AL other* component (e.g. refrigerator, freezer, washing machine, etc.) that relies on electricity as the sole energy source. The distribution of these AL end-use components was shown in Table 6. In contrast, natural gas is the dominant energy source for the DHW end-use. Heating oil is used only in the Atlantic (AT) region and thus plays a minor role.

3.3. Comparison of the CHREM estimates to another model

The CHREM estimates were compared to the top-down Canadian Residential End-Use Model (REUM) estimates published by the Canadian government in the Energy Use Data Handbook [33]. The REUM relies on aggregate energy consumption data reported by Statistics Canada, and allocates this consumption to end-uses based on housing stock characteristics and estimated unit energy consumption.

As with most model comparisons, complications were encountered due to the scoping of the individual models. The CHREM estimates are based on 'average year' weather data supplied by Environment Canada. The REUM uses individual year weather data in constructing estimates to influence the end-uses year to year. Therefore, the REUM data were averaged for years 2000–2004 to account for annual weather variations.

A second complication in comparing the models is related to house types. The CHREM estimates energy consumption only for

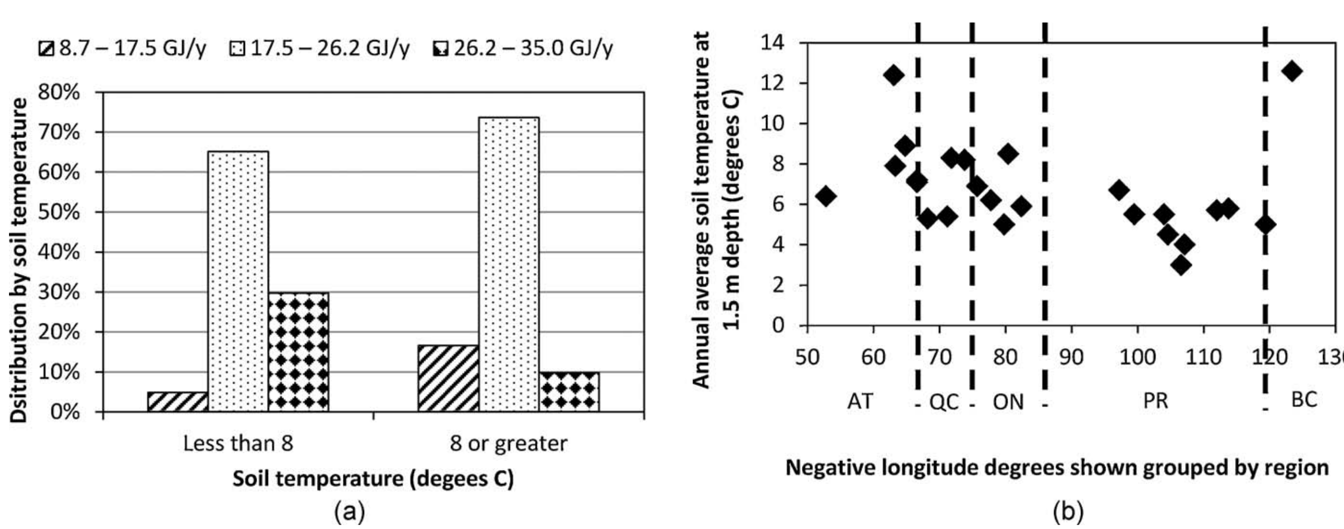

Fig. 7. Annual average soil temperature (1.5 m depth) relationships to (a) DHW energy consumption, and (b) region.

Table 9
Regional and national AL and DHW annual energy consumption estimates by end-use and energy source for SD and DR house types.

House type or region	By end-use		By energy source			Combined (PJ)
	AL (PJ)	DHW (PJ)	Electricity (PJ)	Natural gas (PJ)	Heating oil (PJ)	
SD	205.4	166.1	273.6	93.6	4.3	371.5
DR	42.5	34.7	54.3	22.3	0.6	77.2
AT	24.2	16.1	35.4	0.0	4.9	40.3
QC	47.1	40.4	87.5	0.0	0.0	87.5
ON	86.0	79.7	102.0	63.7	0.0	165.7
PR	43.7	41.9	48.8	36.7	0.0	85.5
BC	46.9	22.6	54.2	15.4	0.0	69.6
Canada	247.9	200.7	327.9	115.9	4.9	448.7
Canada percentage	55%	45%	73%	26%	1%	–

Table 10
National CHREM annual end-use energy consumption estimates by energy source for SD and DR house types.

End-use	Energy source	CHREM	
		Energy consumption (PJ)	Proportion by end-use (%)
AL	Electricity	244.9	99
	Natural gas	3.0	1
DHW	Electricity	83.0	41
	Natural gas	112.9	56
	Heating oil	4.9	2
Combined	Combined	448.7	–

the SD and DR house types. The REUM estimates combined energy consumption by energy source for all house types, including apartments and mobile homes. A scaling method was developed to modify the REUM estimates to be representative of only the SD and DR house types.

In the case of DHW, the REUM also provides estimates of energy consumption by house type, and these values were used to scale the DHW energy consumption by energy source estimates. Table 11 shows the DHW scaling process. Of a total 339.4 PJ, REUM estimates that 237.6 PJ are due to the SD and DR house types, or 70%. The energy source components for the DHW estimates were then scaled by this 70% value, as shown in the final column of Table 11. This process preserves the REUM DHW estimates by house type, and assumes it is uniformly distributed across the energy sources.

In the case of AL, the REUM does not provide estimates of energy consumption by house type. As an alternative, floor area was chosen as an indicator for scaling. A similar process to that shown in Table 11 was employed, although the basis for scaling was the floor area contributions of the SD and DR house types to the national total.

The results of the comparison of the CHREM and the REUM are shown in Table 12. The final column (CHREM/REUM ratio) may be used as an indicator of model agreement. The CHREM estimates a combined 6% more energy consumption than REUM for the DHW and AL end-uses. This is an acceptable level of agreement between the two models, especially considering the CHREM is a bottom-up approach and the REUM is a top-down approach. More significant variations between the model estimates appear as the end-uses are examined individually and by energy source. In particular, the CHREM estimates 34% more AL energy consumption and 26% less DHW energy consumption.

These differences between the CHREM and REUM require explanation. There are a few obvious differences in methodology:

Table 11
Annual energy consumption values used to scale the REUM DHW energy consumption estimates to be representative of only the SD and DR house types.

Original REUM average 2000–2004 DHW estimates				Scaled REUM 2000–2004 DHW estimates for SD and DR house types	
House type	Energy (PJ)	Energy source	Energy (PJ)	Energy source	Energy (PJ)
SD	**199.8**	Electricity	123.0	Electricity	86.1
DR	**37.9**	Natural gas	198.8	Natural gas	139.2
Apartments	94.6	Heating oil	15.7	Heating oil	11.0
Mobile homes	7.2	Other[a]	1.0	Other	0.7
		Wood	0.9	Wood	0.6
Total of SD and DR only	**237.6**	Total of all energy sources	339.4	Total of all energy sources	**237.6**

[a] Other includes coal and propane.

Table 12
National annual end-use energy consumption estimates by load type and energy source for SD and DR house types.

End-use	Energy source	CHREM		REUM 2000–2004		CHREM/REUM ratio
		Energy (PJ)	Dist. (%)	Energy (PJ)	Dist. (%)	
AL	Electricity	244.9	99	181.1	98	1.35
	Natural gas	3.0	1	3.5	2	0.86
	Total	*247.9*	–	184.6	–	*1.34*
DHW	Electricity	83.0	41	86.1	36	0.96
	Natural gas	112.9	56	139.2	59	0.81
	Heating oil	4.9	2	11.0	5	0.45
	Other[a]	0.0	0	0.7	0	0.00
	Wood	0.0	0	0.6	0	0.00
	Total	*200.7*	–	237.6	–	*0.84*
Combined	Combined	448.7	–	422.2	–	1.06

[a] Other includes coal and propane.

- The CHREM attributes the furnace fan and boiler pump components of the space heating plant equipment to the AL. The REUM does not include these components. Such fans and pumps are not insignificant as a typical rating might be 250 W, and it may operate for upwards of 25% of the year (approximately 50% duty during heating season).
- The CHREM does not account for wood or "other" energy sources for the DHW energy consumption. The REUM does estimate these components although they are minor.

The most important difference in methodology between the models is related to the modeling approach and the ability of distinguishing end-use energy consumption. The top-down approach of the REUM relies on aggregate billing data, annual stock appliance assessments (primarily related to sales data), approximate usage profiles, and appliance unit energy consumption. Aggregate billing data does not include unreported energy deliveries, and the use of appliance unit energy consumption is a significant assumption in categorizing occupant behaviour. In contrast, the CHREM energy estimates are based on the bottom-up technique, and capture the interrelation of appliances and occupants via a NN technique. The ability to independently assess end-uses is a strength of the CHREM.

Because of the level of model agreement in total energy consumption of the AL and DHW end-uses, and the strengths and weaknesses of the modeling approaches, the CHREM energy consumption estimates are proposed as a new relationship between these two occupant influenced end-uses.

3.4. Use profiles

The distribution of load profiles selected for incorporating the AL and DHW results into the CHREM engineering method are shown in Fig. 8. The *AL cook stove and other* and the DHW are dominated by the medium consumption levels. This is expected because the ranges were based on Canadian data [27]. In contrast, the clothes dryer is dominated by the low level.

As described in Section 2.5, the CHREM engineering method linearly alters the time-step profile value using a multiplier. The multiplier may be used as a proxy for representativeness of the load profile for a particular house. A value of unity indicates that the annual consumption of the profile is exactly the same as the house. A description of the multipliers is summarized in Table 13. Multipliers for the *AL cook stove and other* and the DHW average close to unity. The dryer multiplier averages only 0.56. This is because the clothes dryer profiles average 3.9, 8.6, and 12.7 loads/week, for the low, medium, and high levels, respectively [27]. The NN input for clothes dryer comes from SHEU 2003, where the levels of loads/week are 0, 1–2, 3–5, and greater than 5. Therefore, it would be advantageous to have a dryer profile at a lower level.

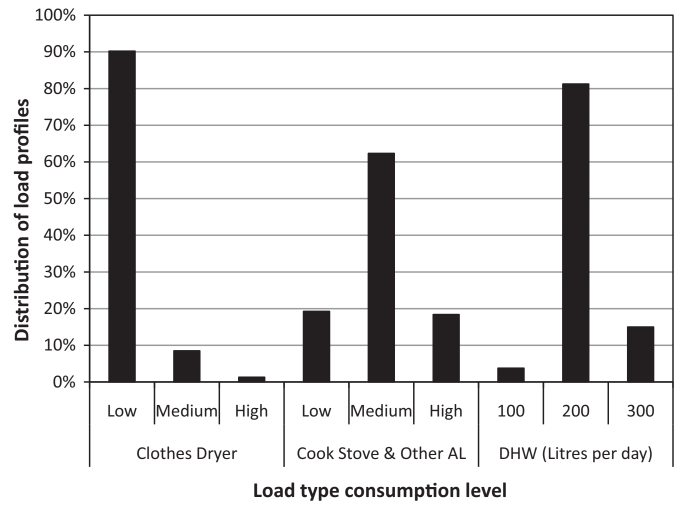

Fig. 8. Selected profile distribution levels for the CSDDRD based on annual AL energy consumption and DHW draw.

Table 13
Characteristics of the multipliers used to equate annual profile consumption with individual house consumption.

Statistic	AL dryer multiplier	AL cook stove and other multiplier	DHW multiplier
Minimum	0.01	0.61	0.75
Maximum	1.74	2.23	1.50
Average	0.56	1.06	1.00
Standard deviation	0.40	0.18	0.14

3.5. Per household and per capita consumption

SHEU 2003 estimates that there are 8.91 million single-detached and double/row households in the five evaluated regions of Canada [23]. Dividing the CHREM estimates by the number of households results in AL and DHW energy consumption of 27.8 GJ and 22.5 GJ per household, respectively, and an annual average daily DHW volume draw of 208 L/day per household.

"Population and dwelling counts" of Census 2006 estimate that there are 31.5 million people in the five regions of Canada [21]. Based on the household structure allocation defined by SHEU 2003, there are 27.5 million people living in single-detached and double/row households. The remaining population lives in apartments or mobile homes. Dividing the CHREM estimates by the number of people results in AL and DHW energy consumption of 9.0 GJ and 7.3 GJ per capita, respectively, and an annual average daily DHW volume draw of 67 L/day per capita.

The CHREM per household and per capita consumption estimates are compared to other published values in Table 14. Perlman

Table 14
Comparison of published estimates of Canadian per household and per capita AL and DHW annual energy and volume draw consumption.

Statistic	Source	AL energy consumption (GJ)	DHW energy consumption (GJ)	DHW volume draw (annual average L/day)
Per household	Perlman and Mills [34]	–	–	239
	Farahbakhsh et al. [5]	31.2	21.6	–
	Aydinalp et al. [8,17]	31.3	26.0	–
	Aguilar et al. [32]	–	–	353
	CHREM	27.8	22.5	208
Per capita	Perlman and Mills [34]	–	–	61
	Aguilar et al. [32]	–	–	139
	CHREM	9.0	7.3	67

and Mills [34] measured the DHW consumption of 58 Canadian houses. Farahbakhsh et al. [5] developed a bottom-up engineering model of the Canadian housing stock based on the SHEU 1993 data. Aydinalp et al. [8,17] used their NN models to assess the energy consumption of the SHEU 1993 dataset that was not used for model calibration. Their AL and space cooling estimates have been modified for Table 14 by removing the specified space cooling electricity consumption. Aguilar et al. estimated DHW consumption by applying scaling factors to total (cold and hot) water consumption [32].

Table 14 shows that the CHREM estimates AL energy consumption to be approximately 89% of previous models. This is likely due to the evolving AL ownership from 1993 to 2003, such as the increased use of energy efficient lighting (e.g. compact fluorescent bulbs). The CHREM estimate of DHW energy consumption is located within the range of other estimates. The CHREM estimate of household DHW volume consumption is 87% of the measured values by Perlman and Mills [34]. This is likely due to evolving DHW device ownership from 1985 to 2003, such as low flow showerheads and tap aerators. It appears the DHW scaling factors used by Aguilar et al. [32] significantly overestimate DHW volume draw in comparison with other estimates.

4. Conclusion

The bottom-up CHREM statistical method, which relies on previously developed NN models, has been used to estimate the national residential energy consumption for AL and DHW of single-detached and double/row houses. These house types comprise 80% of the Canadian housing stock [23]. The CHREM uses unique characteristics of nearly 17,000 houses that are augmented with common appliance and demographic data as input information. The NN method is used to independently estimate the AL and DHW energy consumption, and these results are scaled to be representative of the Canadian housing stock.

The annual total AL and DHW energy consumption of 448.7 PJ was found to be within 6% of a top-down model estimate, an acceptable level of agreement. However, the CHREM finds the proportion of AL energy consumption to be larger than DHW energy consumption, opposite that of the top-down model. Differentiation of the AL and DHW energy consumption is considered a key strength of the CHREM bottom-up modeling methodology as it independently estimates each end-use. Therefore, the CHREM energy consumption estimates are proposed as a new relationship between the occupancy influenced AL and DHW end-uses.

The AL and DHW estimates are used to select appropriate load profiles (e.g. 5 min time-step) and calculate corresponding multipliers for use in the CHREM engineering method. Individual profiles are used for DHW, clothes dryer, cook stove, and remaining AL components. This allows for the allocation of consumed energy to either the interior or exterior of the conditioned zone (e.g. the clothes dryers vents outside) as well as consideration of the appliance energy source (e.g. the clothes dryer and cook stove can be powered by either electricity or natural gas).

The selected load profiles and corresponding multipliers for each of the 16,952 houses is incorporated into the bottom-up engineering method of the CHREM for estimation of space heating and space cooling energy consumption, and finally the determination of greenhouse gas emissions based on emission intensity factors. The engineering method will use certain portions of the AL to offset space heating or increase space cooling energy requirements. It also includes the AL and DHW energy consumption, with the space heating and space cooling energy consumption, to estimate the total for each energy source of each house. These results are scaled to be representative of the Canadian housing stock, and result in a comprehensive residential energy and greenhouse gas emissions model.

Acknowledgements

The authors would like to thank Merih Aydinalp-Koksal of Hacettepe University for graciously providing support for the NN model and answering our questions regarding the input data, Phyllis Ross of Dalhousie University for guiding our access to census data and postal code analysis, and Marianne Armstrong of the Canadian National Research Council for providing disaggregated appliance and lighting profiles.

The authors are grateful for the funding provided by the Natural Sciences and Engineering Research Council of Canada through the Solar Buildings Research Network and through V.I. Ugursal's Discovery Grant.

References

[1] R. Saidur, H.H. Masjuki, M.Y. Jamaluddin, An application of energy and exergy analysis in residential sector of Malaysia, Energy Policy 35 (2007) 1050–1063.
[2] L.G. Swan, V.I. Ugursal, Modeling of end-use energy consumption in the residential sector: a review of modeling techniques, Journal of Renewable and Sustainable Energy Reviews 13 (2009) 1819–1835.
[3] Energy Information Administration, Model documentation report: residential sector demand module of the national energy modeling system, Office of Integrated Analysis and Forecasting, Energy Information Administration, US Dept. of Energy. DOE/EIA-M067, 2005.
[4] J.A. Clarke, S. Ghauri, C.M. Johnstone, J.M. Kim, P.G. Tuohy, The EDEM methodology for housing upgrade analysis, carbon and energy labelling and national policy development, in: Proceedings of eSim, Quebec City, 2008, pp. 135–142.
[5] H. Farahbakhsh, V.I. Ugursal, A. Fung, A residential end-use energy consumption model for Canada, International Journal of Energy Research 22 (1998) 1133–1143.
[6] K. Steemers, G.Y. Yun, Household energy consumption: a study of the role of occupants, Building Research & Information 37 (2009) 625–637.
[7] M. Parti, C. Parti, The total and appliance-specific conditional demand for electricity in the household sector, The Bell Journal of Economics 11 (1980) 309–321.
[8] M. Aydinalp, V.I. Ugursal, A.S. Fung, Modeling of the appliance, lighting, and space cooling energy consumption in the residential sector using neural networks, Applied Energy 71 (2002) 87–110.
[9] K.H. Ozturk, O.E. Canyurt, A. Hepbasli, Z. Utlu, Residential-commercial energy input estimation based on genetic algorithm (GA) approached: an application of Turkey, Energy and Buildings 36 (2004) 175–183.
[10] L.G. Swan, V.I. Ugursal, I. Beausoleil-Morrison, Implementation of a Canadian residential energy end-use model for assessing new technology impacts, in: Proceedings of Building Simulation, Glasgow, 2009, pp. 1429–1436.
[11] Energy Systems Research Unit, The ESP-r System for Building Energy Simulation: User Guide Version 10 Series, Univ. of Strathclyde, Glasgow, 2002. Available from: www.esru.strath.ac.uk.
[12] J.A. Clarke, Energy Simulation in Building Design, Butterworth-Heinemann, Oxford, 2001.
[13] L.G. Swan, V.I. Ugursal, I. Beausoleil-Morrison, A database of house descriptions representative of the Canadian housing stock for coupling to building energy performance simulation, Journal of Building Performance Simulation 2 (2009) 75–84.
[14] S. Blais, A. Parekh, L. Roux, Energuide for houses database – an innovative approach to track residential energy evaluations and measure benefits, in: Proceedings of Building Simulation, Montreal, 2005, pp. 71–78.
[15] M. Aydinalp, V.I. Ugursal, A.S. Fung, Modeling of residential energy consumption at the national level, International Journal of Energy Research 27 (2003) 441–453.
[16] M. Aydinalp-Koksal, V.I. Ugursal, Comparison of neural network, conditional demand analysis, and engineering approaches for modeling end-use energy consumption in the residential sector, Applied Energy 85 (2008) 271–296.
[17] M Aydinalp, V.I. Ugursal, A.S. Fung, Modeling of the space and domestic hot water heating energy consumption in the residential sector using neural networks, Applied Energy 79 (2004) 159–178.
[18] Office of Energy Efficiency, 1993 Survey of Household Energy Use, Natural Resources Canada, Ottawa, 2004.
[19] M. Aydinalp, A new approach for modeling of residential energy consumption, Doctor of Philosophy Thesis, Dalhousie University, Halifax, 2002.
[20] Statistics Canada, Postal Code Conversion File (PCCF) Reference Guide – April 2007 Postal Codes, Catalogue No. 92-153-GIE, Ottawa, 2007.
[21] Statistics Canada, 2006 Census of Population. Ottawa, 2006. Population distribution of census subdivision areas: 97-551-XWE2006013. Household structure: 94-576-X2006001. Families: 97-553-XWE2006002. Population and dwelling counts: 97-550-XWE2006002.
[22] Environment Canada, National Climate Data and Information Archive – Canadian climate Normals, Ottawa, 2009. Available from: www.weatheroffice.gc.ca.
[23] Office of Energy Efficiency, 2003 Survey of Household Energy Use – Detailed Statistical Report, Natural Resources Canada, Ottawa, 2006.
[24] Statistics Canada, 2001 Census of Canada, Ottawa, 2002.

[25] Computing in the Humanities and Social Sciences, University of Toronto, 2009. Available from: www.chass.utoronto.ca through the Data Liberation Initiative.
[26] R. Yao, K. Steemers, A method of formulating energy load profile for domestic buildings in the UK, Energy and Buildings 37 (2005) 663–671.
[27] M.M. Armstrong, M.C. Swinton, H. Ribberink, I. Beausoleil-Morrison, J. Millette, Synthetically derived profiles for representing occupant-driven electric loads in Canadian housing, Journal of Building Performance Simulation 2 (2009) 15–30.
[28] U. Jordan, K. Vajen, Realistic Domestic Hot-Water Profiles in Different Time Scales, International Energy Agency – Solar Heating and Cooling Program, Task 26 – Solar Combisystems, Univ. Marburg, Germany, 2001.
[29] I. Knight, N. Kreutzer, M. Manning, M. Swinton, H. Ribberink, European and Canadian non-HVAC electric and DHW load profiles for use in simulating the performance of residential cogeneration systems, IEA, Annex 42- FC+COGEN-SIM, Subtask A, 2007. Available from: http://www.ecbcs.org/docs/Annex_42_Domestic_Energy_Profiles.pdf.
[30] Electric Power Research Institute, Electric and Gas Range Tops: Energy Performance, Technical Brief, November 2006.
[31] J. Wiehagen, J.L. Sikora, Domestic Hot Water System Modeling for the Design of Energy Efficient Systems, NAHB Research Center, Upper Marlboro, MD, 2002.
[32] C. Aguilar, D.J. White, D.L. Ryan, Domestic Water Heating and Water Heater Energy Consumption in Canada, Canadian Building Energy End-Use Data and Analysis Centre, Edmonton, CBEEDAC 2005-RP-02, 2005.
[33] Office of Energy Efficiency, Energy Use Data Handbook 1990 and 1998 to 2004, Natural Resources Canada, Ottawa, 2006.
[34] M. Perlman, B.E. Mills, Development of residential hot water use patterns, ASHRAE Transactions 91 (Part 2A) (1985) 657–679.