Developing occupant-informed household archetypes in Canada

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Abstract

This paper proposes a novel methodology to enrich the available Canadian residential archetypes with stochastic household profiles derived from statistical databases. The Canadian time use survey (TUS) data is used for developing a stochastic activity-based model to generate energy demand profiles of different households' compositions. The proposed activity model is integrated with a building energy model to estimate household energy consumption, including space heating, appliances load, water heating, and lighting load. The results showed that the occupant characteristics have a significant impact on occupancy hours with difference up to 19% between single working and couple retired households. Moreover, for the influence of energy behaviour, the results showed a 18% difference between energy spender and saver households. The resultant workflow provides a probabilistic building performance distribution for residential buildings that is beneficial for future investigations, such as applicable energy conservation measurements (ECMs), building retrofits, and provide policy-making practices.

Introduction

Approximately 13% of Canadian energy consumption is caused by residential buildings (CER, 2021). Decreasing this energy consumption represents an enormous challenge for ambitious carbon mitigation plans. It requires an in-depth understanding and reliable information of the buildings' energy consumption and potential saving opportunities (Lou et al., 2022). However, acquiring high granular measured data for buildings performance and characteristics needs tremendous resources, especially on the urban level, considering the widespread influential parameters such as (weather, construction material, installed energy systems, and occupant behaviour). In this context, several urban building energy modeling (UBEM) techniques are developed to simulate district or city-scale building stock. The UBEM is categorized into top-down and bottom-up models (Ferrando et al., 2020). Ali et al. (2021) conducted a comprehensive review of the available UBEM methods and approaches. The bottom-up models simulate urban energy consumption by aggregating representative individual buildings' simulation. As such, the bottom-up models showed a better performance in reflecting the variation in the energy performance of individual buildings and more capabilities to obtain high temporal and spatial resolution results (Allegrini et al., 2015). Running an accurate and computationally efficient urban scale model requires a simplification procedure to represent the different features available in the modeled buildings stock. The modelers developed and used a set of archetypes to describe the buildings stock using essential buildings' information such as (function, typology, construction year, installed systems, and schedules) (Fonseca & Oliveira Panão, 2017). Typically, the averaging method is used to obtain the mean value of these features from national surveys and in-site measurements. A weight factor is associated with each archetype to model building stock as a combination of buildings and systems. The UBEM methods and tools have expanded to various applications, including (urban planning, design carbon reduction strategies, building level recommendation, and buildings to grid applications) (Ang et al., 2020). UBEM relies on the standard building energy modeling techniques, a well-established field. However, the challenge becomes in upscaling the building energy modeling (BEM) process. Various studies have demonstrated the effectiveness of using visual scripts for automating a high number of energy simulations, as it parametrizes the static process of the conventional software tools of OpenStudio and EnergyPlus (Saad & Araji, 2021, 2020).While the averaging method is considered sufficient for developing archetypes to the primary annual energy consumption applications, the emerging utilization of UBEM tools in building to grid applications supported the need to consider the heterogeneity of buildings features and occupants' related parameters in the developed archetypes (Ang et al., 2020; Cerezo et al., 2017; Razmara et al., 2017).

In this context, Several studies used the Monte Carlo method to analyze the uncertainty of several building parameters, up to 37 parameters, on the building stock model (Hughes et al., 2013). Booth et al. (2020) showed the improvement in energy consumption prediction accuracy resulted from integrating the uncertainty of buildings and occupants' parameters to the modeled archetype. Ben and Steemers (2020), used different occupants' energy consumption profiles in investigating retrofit options for English residential archetypes. Saad et al., (2022), investigated the uncertainty effect of future building usage types on the viability of energy conservation upgrades to unoccupied building stock in Montreal city. The occupant parameters can be obtained through several sources such as surveys, in-site measurements, and smart meters and thermostats. Osman and Ouf (2021) presented a comprehensive review for using time use survey (TUS) data and models to stochastically simulate occupants' presence and activity in residential buildings. In the Canadian context, Abdeen et al. (2021) studied the impact of occupants' related assumptions on the performance of Canadian archetypes. They showed the overestimation of heating energy following occupants' parameters defined in the national building code (NBC). Hicks et al., (2018) showed the significance of occupant scenarios on the residential building energy performance. Concluding from the aforementioned research, building reliable and representative stock archetypes for future UBEM applications requires a prudent consideration for occupants' characteristics and behaviour uncertainty.

Objective

The shift towards using performance-based compliance codes requires a methodology for evaluating the impact of occupants' uncertainty on the building performance. The commonly used deterministic and fit-for-all occupants' profiles failed to represent the heterogeneity of occupants' characteristics and their impact on end-use energy profiles. Accordingly, this research proposes a methodology to include the occupants' attributes in the Canadian residential archetypes and investigates the expected variation in their energy performance resulting from diversity in occupants' characteristics and energy consumption behaviour. This paper applies the proposed methodology by stochastically simulating five household types with different energy consumption profiles. The generated profiles are used for evaluating the expected variation in the energy performance of a single-family house archetype under Montreal's climate conditions.

Methodology

The following sections list the proposed methodology's main components and describe each component's main assumptions and limitations in detail.

Modeling framework

In this paper, the building information is extracted directly from the Canadian residential archetypes developed by Natural Resources Canada (NRCan). In this study, a combination of building and occupant behavior models took place. First, a usage profile generator (UPG) model was developed, as shown in figure 3. Moreover, the occupants' data is extracted from the Canadian TUS data that provides a vital source for occupants' daily activities in residential buildings. The model generates stochastic profiles in behaviour and is representative of the statistical sample of the population.

The combination between the UPG model and the complete workflow is shown in figure 2. The presented workflow starts by extracting buildings features and characteristics from the archetype. The exported data (i.e., building characteristics) is used to populate an energy model.

Ladybug tools were used to develop the energy model. The parametric overlay was used to facilitate and automate the simulation process for a large number of simulations, reaching 4500 simulation runs. The translation of the building characteristics from HOT2000, which is the native format for the NRCan 11 archetypes, to EnergyPlus included exporting the simulation report of HOT2000 and the extraction of the needed properties to feed in the thermal zones. HOT2000 is a typical Canadian energy simulation tool for energy auditing; however, a caveat to its capabilities is the limitations of its inputs data structures. The missing building information are obtained from ASHRAE and NECB standards. In a consecutive step, the thermal zones were combined into a multi-zone model that is linked with an updated usage profile from the UPG. The integration method was developed in an automated process using the visual scripting tool Grasshopper. Later, the multi-zone model is exported into IDF format, simulated in EnergyPlus, and reported results. Notably, the developed process is preliminary and can receive more improvements in further studies.

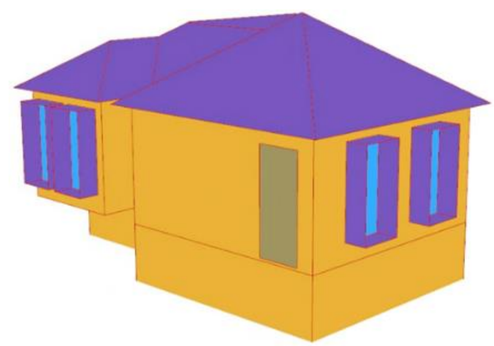

Figure 1 *Energy Model Visualization for the Single-Family House - Detached*

Canadian residential buildings archetypes

Canadian residential archetypes have been initially developed to examine building regulations and codes(Asaee et al., 2019). For the support of energy-compliant housing, Natural Resources Canada (NRCan) developed a set of representative buildings using an averaging statistical methodology to represent the building stock (Asaee et al., 2019). The NRCan known "11 archetypes" were developed, including a variety of residential buildings "attached" and "detached" in type. Their primary use is analyzing building codes feasibility and effects.

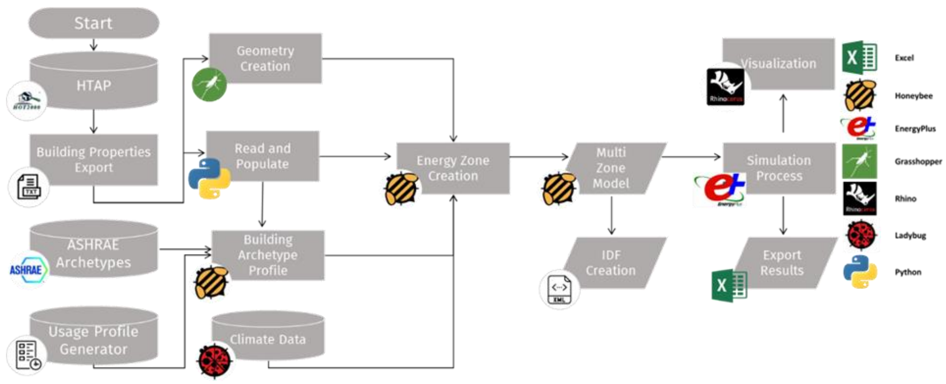

Figure 2 Workflow used for the study methodology

A detached single-family house archetype was used for this study. The typology includes a single ground floor combined with basement space, as shown in figure 1. The total heating space is around 1000 feet^2 and is supplied by a natural gas-based furnace system. Last, the construction year of the building is assumed to be 2011.The building parameters were remained constant in the simulation process.

Table 1 Archetype building properties

Building area (Sq. ft)	1000
Location	Montreal
Orientation	Facing East
Heating system	Natural gas furnace
Cooling system	AC Window Unit.
Exterior Wall RSI (m^2K/W)	3.31 – 3.64
Windows RSI (m^2K/W)	0.488 – 0.538

Households' archetypes

The heterogeneous nature of the occupants' characteristics leads to an infinite number of profiles to represent it. Therefore, for simplification purposes, a set of household archetypes are defined and extracted from Canadian TUS data. The TUS raw data is filtered based on the following occupants' features (gender, age, occupation, household size, and household type) and used to form a set of occupants' archetypes. In this paper, five typical archetypes of households are defined to represent different compositions available in the population, namely, (single working, single retired, couple working, couple retired, typical family, and shared household).

Type 1 and Type 2 represent households inhabited by either a single or retired person, representing 14% of the population. In addition, *Type 3* and *Type 4* represent 26% of the population. The defined typical family (*Type 5*) consists of two parents and a maximum of three children regardless of their age or gender (24% of the population).

Table 2 shows the selected occupants' archetypes and the characteristics of each type.

Occupant type	**Typology**	**Age**	**Occupation**	**Household size**	**%**
Type 1	Single Working	25-54	Full time working/ student	1	14 %
Type 2	Single Retired	64-72	Retired	1	
Type 3	2-working members	25-64	Full-time working/ student	2	26 %
Type 4	2-retired members	64-74	Retired	2	
Type 5	Typical Family	15-72	All	4-5	24%

Table 2 Occupants' characteristics archetypes

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Households' energy behaviour archetypes

The households' energy archetypes represent the different energy demand behavioural patterns. In this paper, three basic behavioural archetypes are defined as (1) saver user, (2) average user, and (3) spender user. Table 3 shows the behaviour variables of each occupants' type, including 1) space heating and cooling set-points 2) space heating/cooling set-back, 3) heating/cooling systems schedules, 4) lighting technology and schedule, 5) use of appliances, and 5) DHW usage and preferred temperature (Ben & Steemers, 2020). The behavioural variables assumptions are based on information obtained from the Canadian household energy use survey (SHEU-2015) (*NRCan*, 2015), statistics for major appliances used in Canada (NRCan, 2018), and reported information in literature (Abdeen et al., 2021; Armstrong et al., 2009; Ben & Steemers, 2020; Hicks et al., 2018). Using these descriptive occupant archetypes gives the opportunity for tailoring and optimizing the future energy conservation measurements according to the characteristics of each household (Ben & Steemers, 2020).

Table 3 Occupants' energy use archetypes

Parameters	**Saver user**	**Average user**	**Spender user**
Heating set-point	21°C	22°C	23°C
Heating set-back	15°C	18°C	21°C
Cooling set-point	23°C	22°C	21°C
Cooling setback	28°C	26°C	24°C
Lighting	LED bulb	Florescent bulb	Incandescent bulb
Appliances	Energy star	Average	Outdated
DHW	Half consumption	Standard consumption	Doubled consumption

Occupant behaviour modeling

The Canadian TUS data is used to model occupants' presence and activities. First, the TUS dataset is pre-processed by categorizing the reported activities into outdoor and indoor activities. The outdoor activities are simplified into three main states (transport, work, and absent), as shown in figure 3. The indoor activities are simplified to 8 descriptive energy-related activities, as shown in Figure 3. The TUS data is used to calibrate an inhomogeneous event-based Markov chain model to generate occupants' stochastic profiles based on their characteristics. The details and verification of the developed TUS-based model are presented by (Osman & Ouf, 2022).

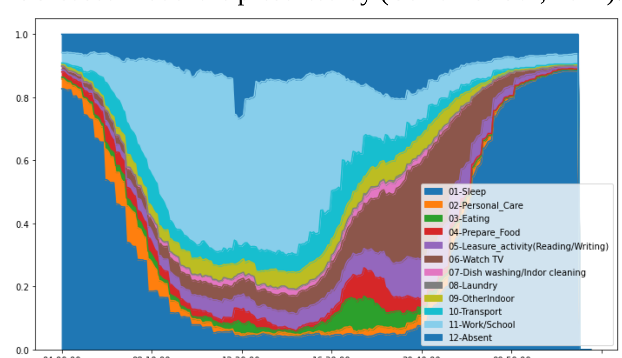

Figure 3 Visualisation of aggregated TUS-based activities profiles

Number of iterations and convergence criteria

The Monte Carlo model uses a set of random iterations to achieve the convergence of the results. Therefore, it is necessary to calculate the minimum required number of iterations by applying the following procedure developed by (Oliveira et al., 2018): (1) the model randomly generates 100 user profiles; (2) the frequency values for different indoor, and outdoor activities are computed; (3) the model randomly generates additional ten batches until the impact of the batch on the calculated probabilities is below 5%.

Activity and presence modeling

The developed TUS-based model generates 150 yearly occupancy and activities profiles with 5 minutes resolution. The generated profiles consider the different occupants' characteristics and the distinction between weekdays and weekends. Later, the generated profiles are used in a set of sub-models to estimate the energy impact of the reported activities, as explained in the following sub-sections.

Lighting demand modeling

Occupancy status and irradiance data are used to develop a stochastic model for estimating household lighting demand. First, the occupants' activities generated by the previously described Markov-chain model are simplified into three main activities related to lighting demand 1) absence, 2) active presence, and 3) sleeping. The model assumes that the lightings can only be switched on during occupants' active presence times. Second, the precepted indoor illumination level affects the occupants' willingness to switch on the light, which depends on several factors related to rooms' properties (geometry, orientation) and windows' size and location (Widén et al., 2009). The light switch-on probability is determined based on a threshold global irradiance to simplify the model. For each household, a normal distribution threshold of 60 W/m^2 and standard deviation of 10 W/m^2 is selected to represent variation in visible light and occupants' preferences (Richardson et al., 2009). The model assumes a unified technology installed in each household based on the occupants' energy archetype as shown in Table 3. The average number of lighting bulbs in a typical Canadian house is around 25 (Hicks et al., 2018). As such, the model assumes the number of switched-on bulbs at each time step based on available irradiance and the number of occupants.

Appliances and plug load

The stochastic activities profiles generated by the TUS-based model are used to develop a high-resolution appliance model. By relating appliances with stochastic occupants' activities profiles, the uncertainty of appliances demand along the day could be introduced to the building energy simulation, which are the main target of this research.

First, a set of appliances is assigned to the household based on their energy profile, as shown in Table 3. The main difference is the energy rate of the used appliances. The model assumes a set of energy-efficient appliances for the energy saver user. On the other hand, the model assumes an extreme case in the energy spender user with outdated appliances and wasteful thermostat behavior. The appliances' power demand details are extracted from statistics of major appliances used in Canada (NRCan 2018) and energy star products (EPA and DOE 2022) as shown in Table 4.

Table 4 Appliances' load based on occupants' energy profile

	Energy star	Standard	Outdated
Refrigerator (W/h)	56	84	120
TV (W/h)	57	100	250
Coffee maker*	240	560	1300
Microwave*	900	1500	2100
Range*	2500	3000	4500
Toaster*	900	1500	1800
Computer and electronics (W/h)	[50-250]	[100-500]	[200-1000]
Clothes washer (W/cycle)	330	470	840
Dryer (W/cycle)	1800	2100	3200
Dishwasher (W/cycle)	930	1250	1500

** There is no energy star label for residential ranges, ovens, microwaves, and coffee makers. The selected values represent energy-efficient appliances available in 2022.*

The generated activities are mapped to related appliances, as shown in Table 5. The model categorizes appliances' switch-on status based on the activity nature into discrete and continuous status. For example, the laundry activity is connected with a washing machine and dryer activation. The model switch-on the washing machine for 1 hour after at the end of the occupants (filling the laundry machine) activity. The dryer cycle only starts at the end of the washing machine cycle. On the other hand, the refrigerator load is not related to the occupants' status, so the model assumes a set of repeated cycles of 30 min distributed randomly along the day with a total of 20 hours. In addition, the model defined a set of dependent loads, which directly related to occupants' activities. For example, watching TV or studying activities are directly related to TV and computer loads. Occasionally, the generated activities from the TUS-based model need more details about their energy use intensity. For example, cooking could be a high-intensity activity that includes (oven, microwave, or range) or a low-intensity activity that use (toaster, coffee maker, or microwave). In the proposed model, the model differentiates between reported cooking activities based on their duration and daytime. The morning and less than 20 minutes cooking activities are assumed to be low intensity (breakfast), while the long and afternoon activities are assumed to be high intense (dinner or lunch), as shown in Table 5. The model generates a high-resolution demand profile for each appliance with five-minute time steps. The generated energy demand of each appliance is then aggregated to an hourly resolution to be suitable for EnergyPlus calculations.

Table 5 TUS activities and related appliances

Activity	Related appliances
Cooking	Breakfast (Microwave, coffee maker, toaster) Dinner (electric range, oven, microwave)
Laundry and ironing	Washing machine, dryer, iron
Cleaning	House cleaning (vacuum machine) Dish cleaning (dishwasher)
Leisure time	TV, computer
Study	Computer, lighting

Domestic hot water demand

This model assigns a water tapping profile to different occupants' activities to estimate their total DHW demand. The tapping profile is defined based on several influential parameters such as required temperature, volume flowrate, and activity duration. The TUS-based model generates the activities in general form, which requires setting a set of assumptions for estimating the hot water consumption resulting from each activity. These assumptions are based on data extracted from national statistics and literature review. For example, the personal care activity could mean (shower, bath, or other activities). These activities have their own nominal temperature and flow rate, as shown in Table 6. This model converts the personal care activity to shower or bath consumption based on duration and total occurrence number during the week. The shower time assumed to be between 6 to 10 minutes. Meanwhile, the number of shower activities are assumed based on the correction function derived from the total number of showers per week reported in Canadian energy use survey (NRCan 2015).

In addition, the model relates three more activities with DHW consumption, namely, cooking, laundry, and cleaning. The cooking activities are converted to DHW consumption based on assumptions reported in the Building America benchmark report by sampling from an exponential distribution with 4.3 l/min and a standard deviation of 2.3 (NREL 2010). The laundry is converted to DHW consumption by relating the activity with the required water consumption of each cycle, as shown in Table 6. Similarly, the dish cleaning activities are converted to DHW consumption based on reported consumption per cycle, as shown in Table 6.

Table 6 Domestic hot water consumption by end-use

Utility	Saver user	Average user	Spender user
Shower (l/min)	6.5	9.5	12
Bath (l/min)	5.6	8.3	11
Clothes washer (l/cycle)	49	87	113
Dishwashing (l/cycle)	11	28	37

Space heating and cooling

The building's space heating and cooling (SHC) load is influenced by the building's characteristics (area, envelopes, windows, etc.) and occupants' parameters (occupancy, heating/cooling set-points- heating/cooling set-back, etc.). In this project, the buildings' SHC is calculated using EnergyPlus as described in the workflow shown in figure 2**Error! Reference source not found.**. The stochastic occupants' profiles generated from the previously described models (occupancy, lighting, appliances, and DHW) are used as occupants' inputs to the SHC model, as shown in figure 2**Error! Reference source not found.**. The occupants' models influence the buildings' energy use intensity (EUI) directly through (lighting, appliances, DHW) or in-direct way through internal heat gain from (occupants, lighting, and appliances latent heat). The model generates the EUI of the building under different occupants' activities and behaviour profiles.

Households and shared activities

The TUS-data and related models are individual-based, which means they generate occupants' activities without considering the interactions with other household members. This research developed a set of households' archetypes that require a reliable assumption for the shared activities to avoid overestimating related energy demand. The developed models randomly link different profiles together as households' members. Later, as a primary assumption, the occupants' activities in the shared household are categorized into tasks and activities, as shown in table 7**Error! Reference source not found.**. The task category will be conducted by only one of the household members. For example, laundry or the use of a washing machine and dryer will be counted only one time per day for the household. The shared category represents the loads or activities that are normally shared between household members (e.g., lighting, leisure time). Accordingly, the model registers the maximum assumed load between different household members during the same time. On the other hand, the single category represents the activities typically conducted individually (e.g., personal care).

Results

The occupancy, lighting, appliances, and DHW consumption profiles are generated individually and then combined and used as inputs for EUI calculations in the EnergyPlus model. In the absence of real energy consumption data, the proposed methodology is validated in two steps. The first step, verification of TUS-based activity model in comparison with TUS data as shown in (Osman & Ouf, 2022). The second step, comparing the average energy consumption load with the data presented in energy survey (SHEU-2015). The developed TUS-based model generates 150 profiles with a stochastic variation, as shown in Figure 4 and Figure 6. First, the occupancy model showed the significance of considering the occupants' type on the estimated occupancy hours. Single working occupant households' average yearly occupancy hours are around 5544 hr./yr. (63% of the year). Meanwhile, the couple's retired household will have around 7234 hr./yr. Occupancy hours (82% of the year). This variation in the occupancy hours percentage directly impacts the SHC, lighting, and appliances loads. In addition, within the same households' archetype, the stochastic profile generator showed the expected variation in the occupancy hours where the variation reached up to 13% in the couple working household. Second, for lighting demand, the results showed that the variability in occupancy hours significantly changes the estimated load where the yearly lighting demand could vary by 38% between (577 - 1494 kWh/yr) by changing the occupant archetype from single working to a retired couple, as shown in Figure 5. Third, the appliances load of the average consumer-type showed a similar pattern. The stochastic appliance model estimated a significant variation in the appliance loads up to 61% resulting from changing the archetype from single working to a couple retired, as shown in Figure 6.

Table 7 Categories of load and activities

Activity/load category	Description
Task	Laundry, cleaning, and cooking
Shared	Leisure time, lighting, eating
Single	Personal care

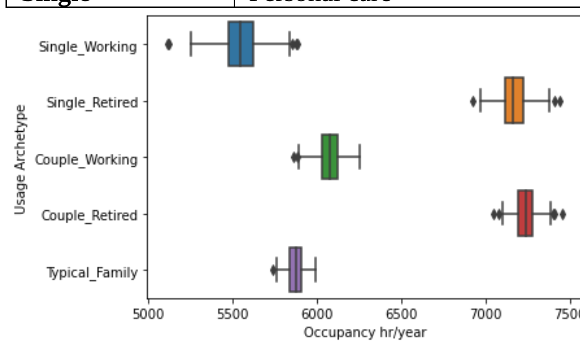

Figure 4 yearly occupancy hours for different households' archetypes

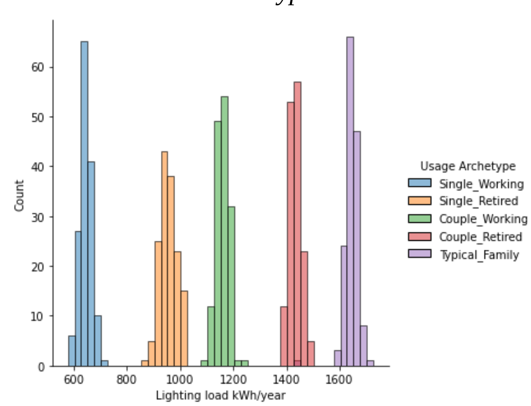

Figure 5 yearly lighting load for different households' archetypes

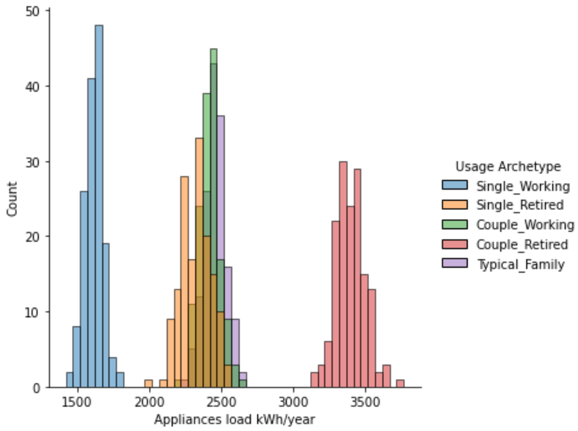

Figure 6 yearly appliances load for different households' archetypes

Error! Reference source not found. Figure 7 shows the interquartile range (IQR) of the saver archetype' EUI where the couple retired was highest among all occupants' archetypes with a mean equal 256 kWh/m^2. Yr. The lowest EUI was reported for the single working household with a mean equal to 211 kWh/m^2. Yr. Moreover, the influence of using stochastic profiles showed the strongest influence on the single retired household where the annual EUI varied by 6% between 227 kWh/m^2. yr. and 240 kWh/m^2. yr., as shown in figure 7**Error! Reference source not found.**.

Concerning the energy behaviour archetype, the results showed that considering energy consumption behaviour significantly impacts the estimated annual EUI for the same building and occupants' archetype. **Error! Reference source not found.** Figure 8 shows a sample for the results comparing the estimated EUI of single working and couple retired households. The results showed that the mean EUI of the single working household increased from 184 kWh/m^2. yr. to 249 kWh/m^2. yr. by changing the energy consumption from saver to spender. Similarly, the couple retired household annual EUI increased by 18% between saver and spender households.

Conclusion and future work

The Canadian TUS data is used to develop a stochastic usage profile generator in this research. The model generates presence and activities profiles for five different households' archetypes. The generated profiles are used in a set of sub-models to estimate the energy demand of the generated households. Moreover, three types of occupant energy consumption behaviour are developed to investigate the impact of occupants' choices on the buildings' EUI. The generated profiles are integrated with a single-detached house archetype to investigate the influence of occupants' uncertainty on the estimated annual EUI. Although the EUI uncertainty resulted from occupant with same characteristics was limited, the results showed the significance of considering the occupancy hours characteristics and energy behaviour of different occupant's archetype. The retired couple household showed the highest occupancy hours and energy loads among the developed households' archetypes. In future work, uncertainty analysis will be conducted on the occupants and buildings' characteristics to investigate the most influential parameters on the annual EUI. The proposed approach showed the significance of considering the occupants' characteristics and behaviour. The significance of this study is allowing future studies to include more detailed and specific archetype models. Studies involving building energy retrofits can capitalize on studying more accurately and developing customized building energy upgrade measures based on household characteristics. Following the proposed methodology, the households will select the optimum affordable and impactful retrofit measure that matches their energy demand. Finding the optimum retrofitting option and reliable estimation of their impact will enhance the Canadian efforts in minimizing the GHG emissions and achieve the 2050 energy targets.

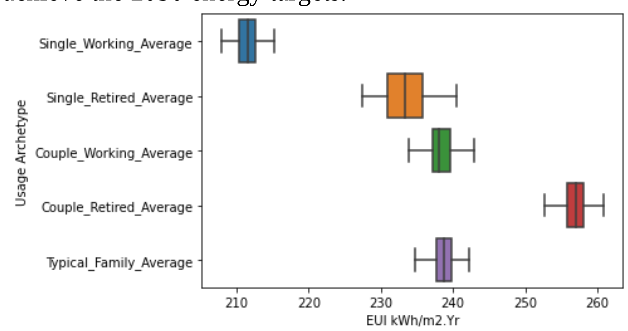

Figure 7 distribution of EUI for different occupants' archetypes

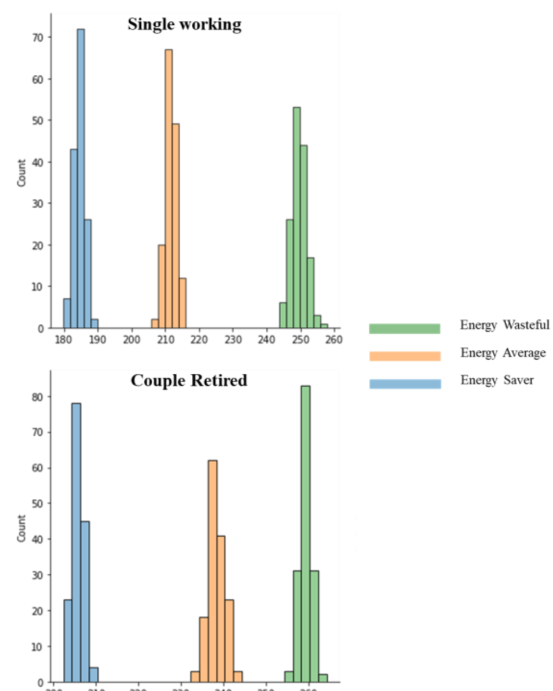

Figure 8 impact of energy behaviour on annual EUI

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