



Occupant-based energy upgrades selection for Canadian residential buildings based on field energy data and calibrated simulations

Anber Rana^a, Piylaruwan Perera^a, Rajeev Ruparathna^b, Hirushie Karunathilake^c, Kasun Hewage^a, M. Shahria Alam^a, Rehan Sadiq^{a,*}

^a School of Engineering, The University of British Columbia, Okanagan Campus, 1137 Alumni Avenue, Kelowna, BC, V1V 1V7, Canada

^b Faculty of Engineering, University of Windsor, 401 Sunset Avenue, Windsor, Ontario, N9B 3P4, Canada

^c Department of Mechanical Engineering, University of Moratuwa, Katubedda, Moratuwa, 10400, Sri Lanka

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ABSTRACT

Occupant behavior in residential buildings has a direct impact on the effectiveness of energy-saving measures. In order to realize a buildings' carbon mitigation targets, the impact of individual occupancy profiles needs to be integrated with building simulation models. This paper introduces a decision support framework as a potential solution to make energy performance upgrade choices based on different occupancy profiles. This framework has been demonstrated through a case study of two single-family detached homes in Canada, which were highly instrumented with sensors for monitoring energy input and output. The case studies represented two common occupancy profiles-(1) a family of four (consisting of 2 working adults and 2 teenagers); and (2) a retired couple. Firstly, calibrated energy models were developed by using one-year energy use data collected through an intrusive load monitoring technique. Secondly, energy upgrade combinations were considered for each profile and tested for additional investment, payback period and greenhouse gas (GHG) emissions. Lastly, the most suitable combination of energy upgrade for each profile was ranked using a multi-criteria decision-making method (e.g., TOPSIS). Results indicated that the retired couple used more energy than the family of four and required energy upgrades with usually higher payback periods to achieve the same level of GHG emission reduction. The results of this research are timely for energy policymaking and developing best management practices, which need to be implemented along with the deployment of more stringent building standards and codes.

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1. Introduction

Globally, the building sector is responsible for consuming 40% of all primary energy and is a major contributor to Greenhouse Gas (GHG) emissions (IEA, 2016). Residential buildings alone are responsible for 17% of the total end-use energy and produce 14% of the national GHG emissions (NRCAN, 2016). The use of energy performance upgrades (EPU) can effectively reduce energy use and GHG emissions in buildings (Asadi et al., 2014). In addition to providing energy efficiency benefits, EPUs can improve thermal

comfort (Ascione et al., 2015; Mauro et al., 2015), indoor air quality (Che et al., 2019; Jin et al., 2012) and health of the occupants (Sharpe et al., 2019). At urban and national scales, EPUs in buildings can impact the efficiency and effectiveness of energy policies and help in reducing energy poverty (Webber et al., 2015). Similarly, carefully implemented EPUs can increase buildings' energy flexibility and pave path for successful deployment of demand response and smart grid programs (Mancini and Nastasi, 2019).

EPUs include improvement in buildings' envelope characteristics, use of energy-efficient equipment and appliances, use of renewable energy systems and change in occupant behavior. EPUs can be selected based on a reduction in energy and GHG emissions evaluated through Building Energy Simulation (BES) models (Clarke, 2007). However, a number of studies have shown that energy savings predicted through BES do not always translate into actual savings (Blight and Coley, 2013; Martinaitis et al., 2015). In order to make informed decisions, it is essential that BES models

* Corresponding author. School of Engineering University of British Columbia, Okanagan 3333 University Way, Kelowna, British Columbia, V1V 1V7, Canada.

E-mail addresses: anber.rana@alumni.ubc.ca (A. Rana), piylaru1@mail.ubc.ca (P. Perera), rajeev.ruparathna@uwindsor.ca (R. Ruparathna), hirushiek@uom.lk (H. Karunathilake), kasun.hewage@ubc.ca (K. Hewage), shahria.alam@ubc.ca (M.S. Alam), rehan.sadiq@ubc.ca (R. Sadiq).

Abbreviations

AIMS	Alberta Air Infiltration Model
APP	Appliances upgrade
ATH	Advance tech home
BC	British Columbia
BES	Building energy simulation
DHW	Domestic hot water upgrade
dLL ₃₀	Change in life cycle cost over 30-year period
EPU	Energy performance upgrades
FN	Foundation wall upgrade
GHG	Greenhouse gas emission (kgCO ₂ -eq.)
HVAC	Heating, ventilation and air conditioning
IC	Initial capital costs
ICF	Insulating concrete foam

ILM	Intrusive load monitoring
LED	Light emitting diode
MBE	Mean Bias Error
MCDM	Multi-criteria decision making
OB	Occupant behavior
PBT	Payback time
PV	Solar photovoltaic system
RF	Roof insulation upgrade
RMSE	Root Mean Square Error
SFDH	Single-family detached home
STH	Standard home
TOPSIS	Technique for order preference by similarity to an ideal solution
WL	Wall insulation upgrade
WN	Window upgrade

represent realistic energy use for evaluating EPU; hence, achieve the desired energy and GHG mitigation targets.

1.1. Occupant behavior (OB)

A growing body of literature recognizes occupant behavior (OB) as the major reason for a gap between actual and simulated energy use of a building (Cali et al., 2016; Sun and Hong, 2017). OB is a major area of interest within the field of building energy performance. OB includes occupancy period, occupant movement and their interactions with the buildings' systems and appliances (Yan et al., 2017).

Literature indicates that ignoring the impacts of actual OB can result in an over prediction of savings from the energy upgrades. Eguaras-Martínez et al. (2014) examined impacts of OB in energy simulations results for a commercial building in Spain. In this research, data collected through surveys was used to generate occupancy number, times and operation schedules of lighting and equipment. It was found that upgrading default energy model with occupant data alone can yield up to 30% difference in energy use compared to the default settings (Eguaras-Martínez et al., 2014).

Detailed monitoring studies further affirm the significance of OB for obtaining realistic BES results. Bahaj and James (2007) performed a comparative study on nine identical homes using monitored data of electricity generation and consumption from photovoltaics. Influence of occupants' awareness regarding energy use behavior, energy tariffs, subsidies and time of usage of appliance were considered for generating energy load profiles. Their results show that occupants' behavior is responsible for energy consumption differences which can be as high as 80% for certain months (particularly for July and December) of the year. Similar impacts from OB for energy models results were shown by Saldanha and Beausoleil-Morrison (2012) study on 12 Canadian homes. Analysis of the monitored data illustrated that HVAC energy use difference with consideration of OB is doubled even for homes with same vintage, sizes and number of occupants.

Motuziene and Vilutiene (2013) investigated the impact of four different occupancy profiles on heating, HVAC auxiliary (fans and pumps in HVAC system) and lighting loads, for residential building in Lithuania. The study showed that compared to default occupancy (family of four) present in BES tool, the three new realistic occupancy profiles (household with the working couple; a household with retired couple; and a household with two working adults and 2 school going children) yield notable variation in energy

consumption. Occupancy profiles affected all three energy loads but the highest variation of 27% was observed for the heating loads.

De Wilde (2014) determined the energy consumption difference in measured and simulated model for a campus building in Plymouth, United Kingdom. De Wilde (2014) study also considered the impact of uncertainties possible in measurement and prediction. The results showed that energy model results over predicted gas consumption by 5% while under predicted electricity up to 30%. These and similar studies highlight the significance of OB impact on energy calculations. Similarly, in order to select EPUs for buildings, the impacts of OB need to be incorporated in BES models.

1.2. Energy monitoring studies on residential buildings

Residential buildings consume a significant portion of energy and hence are an important focus of energy-saving policies and programs. New residential buildings, in particular have a higher potential for energy efficiency improvement (Amecke et al., 2013), and are used for meeting higher carbon mitigation targets. Studies have also shown that larger savings from energy-saving programs are possible if they are tailored to different household groups (Guerra-Santin, 2011). In the same vein, there is an urgent need to reduce uncertainties associated with OB in order to achieve comfortable indoors (Mavrogianni et al., 2014). In contrast to commercial buildings, there is much less information about the effects of OB in residential buildings (Delzendeh et al., 2017). To date, there are few studies that have used monitored data to generate energy model for low-rise residential buildings (Delzendeh et al., 2017; Lomas, 2010); and consequently, a limited understanding of the impacts of OBs on EPU selections.

In Canada, energy monitoring studies on residential buildings have mostly focused on old buildings constructed prior to implementation of the current more stringent building energy codes, such as NECB-2015, BC Energy Step Code 2017. Saldanha and Beausoleil-Morrison (2012) focused on residential buildings in Ottawa, Ontario constructed between the 1930s and 1990s. A recent energy-monitoring study on Gemini home, Toronto, Ontario is performed on a retrofitted home originally constructed in 1879 (Rumeo, 2019). Other studies have generated energy models based on data collected through interviews and surveys (Cosar-Jorda, 2018; Newsham and Donnelly, 2013). Results from survey studies are able to present impacts of OB on energy use but are not good at predicting energy savings due to EPUs (Richardson et al., 2010; Swan and Ugursal, 2009).

Degree of accuracy of BES can be determined through calibration process (Raftery et al., 2011). In regard to EPU's performance, measurement and verification (M&V) protocols define procedure and calibration limits for BES validation (Ruiz and Bandera, 2017). Most common metrics used for checking calibration are Mean Bias Error (MBE), Normalized Mean Bias Error (NMBE), Root Mean Square Error (RMSE), and Coefficient of Variation of Root Square Mean Error CV (RMSE) (Carratt et al., 2020). Despite the presence of advanced sensors, monitoring systems and calibration metrics, there are limited studies that have used data-driven calibration models for single family homes. Majority of the research on BES calibration has been focused on office buildings (Shiel et al., 2018) or multi-unit residential buildings (Cuerda et al., 2020; Guerra-Santin et al., 2018). Mahar et al. (2019) work focused on designing comfortable indoors through incorporation of energy efficiency measures for a single family house in Pakistan. Data from a questionnaire survey and monitoring of house temperature and humidity was used to calibrate model in EnergyPlus. Two metrics, NMBE and CV (RMSE) for hourly data, were considered for calibration (Mahar et al., 2019). Guiterman and Krarti (2011) developed calibrated model in eQuest tool for low-income housing through 2-year utility energy use data, energy auditing and indoor temperature monitoring. The results from calibrated model were used to select retrofits for the housing units. They used MBE and RMSE thresholds for monthly data. Same metrics were used by Rakhshan and Friess (2017) for calibrating residential buildings in Dubai. They used one-year utility data and results of BES model constructed with DesignBuilder tool. These and similar studies indicate necessity of having more monitored studies that show the influence of occupant behavior on energy use and consequent impact on EPU's performance.

1.3. Paper contribution

The main objective of this study is to investigate the possibility of catering to the energy demand of a new residential building according to expected occupant behavior (specifically occupancy profile) and compare energy performance upgrades that can reduce this energy demand. To meet this objective, a decision support framework is developed that ranks the best energy performance upgrades for a specific occupancy profile. The framework is demonstrated for two single-family residential buildings as a case study in Canada. In particular, this paper (1) develops calibrated models using one-year monitored data for predicting energy use associated with individual occupancy profile; (2) applies the calibrated model to evaluate various energy upgrade options to generate savings in energy costs, payback time (PBT) and reduction in GHG that provides a holistic view, and lastly (3) enables prioritization of different upgrades through application of Technique for order preference by similarity to an ideal solution (TOPSIS) (Hwang and Yoon, 1981) with a variable weighting scale to enable flexibility in defining user preferences.

This study provides an important opportunity to advance the understanding of the impacts of occupancy profiles through the use of detailed monitored energy use data that can help make informed decisions for energy improvements in residential buildings. The relevant results obtained from this study will be useful for proposing suitable EPU's in homes with similar occupancy profiles. This framework can facilitate informed decision making for the home-owners, home-occupiers, and developers. In particular, the energy upgrades that this study recommends for age groups and the size of a household will be useful for policy-makers and utility companies in improving energy conservation policies and associated financial incentives. The framework also provides flexibility to choose between pro-environmental and

pro-economic choices of energy upgrades with different occupancy profiles; therefore, accounting for perspectives of different types of investors.

2. Methodology

In this study, a framework is developed to identify the most appropriate energy performance upgrades for new residential buildings with expected occupancy profiles. The framework shown in Fig. 1 has two main phases: (1) Data Collection and (2) Data analysis.

2.1. Data collection and processing

The two key sources of data include: (1) literature-based data that was used to identify potential energy upgrades; and (2) data captured from the field monitoring system to create calibrated energy models.

The main sources used for literature were peer-reviewed articles and technical reports related to residential building energy and cost modelling. A thorough literature review was performed for current building energy standards for residential buildings, energy and cost modelling methods, energy monitoring techniques, occupancy profiles, and energy performance upgrades possible for residential buildings. Energy performance upgrades can be categorized into three categories: (1) passive, (2) active and (3) renewable energy upgrades. Passive energy upgrades make use of non-mechanical techniques in order to maintain comfortable indoor temperatures and environment while reducing building energy use (Kamal, 2012). Improvements in thermal mass, thermal insulation, upgrade of fenestration systems or the use of green roofs are some examples of passive.

Energy systems. Active energy upgrades employ decreasing operational use of energy through the use of a more efficient system and equipment or change in occupant energy usage behavior. Renewable energy upgrades for residential buildings include the use of geothermal heat pumps, roof photovoltaic systems, etc. Multi-criteria decision-making (MCDM) methods available for ranking and prioritization of energy upgrades were also explored. The collected information was used for developing preliminary energy simulation models, calibrating and validating models, analyzing the effects of energy performance upgrade combinations, assessing associated life cycle costs, PBT and GHG emission reductions, and finally prioritizing the most appropriate upgrades for a specific occupancy profile.

The intrusive load monitoring (ILM) method is proposed for collecting energy use data related to the occupancy profile. ILM method monitors energy use through individual devices with sensing monitors distributed within the building (Ridi et al., 2014). Contrary to the non-intrusive method, the data obtained from ILM are more accurate and helps generate better energy models. ILM method needs a detailed introduction of thermal, humidity and energy sensors to generate energy use behavior of the residential building's systems and equipment. This method enables high degree calibration of preliminary energy model that generates realistic energy use profile and provide practical solutions for EPU options. The design and installation of energy data monitoring are beyond the scope of this research work and should be designed with consultation of building developers, owners and data monitoring experts.

2.2. Data analysis

2.2.1. Energy modelling

A preliminary energy model was developed to determine the



Fig. 1. Proposed framework of evaluation of upgrades for SFDH.

end-use energy demand of the residential building under study. HOT 2000V15.1, a simulation tool developed by CANMET Energy Technology Center was used to generate the model. HOT2000 is tailored for residential buildings in Canada (NRCan, 2019a) and hence ideal for assessing the operational energy use of low-rise residential buildings in Canada. The data needed to generate a standard energy model includes location, house geometry, building envelope characteristics, energy systems, equipment, number of occupants and their hours of occupancy.

HOT2000 is a gray-box program that uses a series of coupled time-dependent steady-state models to determine the energy demands of the house (Logue et al., 2016). This tool uses a modified bin based method and long term monthly weather files for determining the energy performance of the residential buildings (Haltrecht and Fraser, 1997; Parekh et al., 2018). In the bin method, the loads of the house are determined by utilizing steady-state models that are based on the assumption that the temperature remains the same within each interval and the loads can be

expressed as linear functions of outdoor temperatures (Ionesco and Balota, 2013; Peng et al., 2009). HOT2000 divides the house into three energy zones (i.e. attic, main floors and basements) and uses Alberta Air Infiltration Model (AIM2) and Mitalas method to determine the monthly and annual energy loads (Haltrecht et al., 1999). AIM2 model evaluates the infiltration and interaction of wind and stack effects with mechanical ventilation. The infiltration is found by the pressure difference in the windward side of the house and indoors; hence, all the possible openings that can cause infiltration are accounted in the model (O'Brien, 2011). Mitalas method calculates heat losses from the foundation to the soil. It is also capable of accounting the seasonal variation in soil temperature that affects heat losses as well as the impacts of insulation configurations (Haltrecht and Fraser, 1997; Naidj, 1998). The tool also considers the impact of internal heat gains and solar transfers among the three zones for calculating heating and cooling loads. HOT2000 uses part load factors and on and off cycles to determine the size of the heating system (Haltrecht et al., 1999). The tool tests the energy performance using monthly steps and owing to its steady-state nature cannot be readily used for dynamic simulations such as a change in the solar system and wind energies. Despite its limitation as giving loads in monthly time steps the tool is a good predictor of annual net energy performance and is periodically upgraded and tested with other tools for validation (Naidj, 1998; O'Brien, 2011).

Calibration is defined as measure of accuracy of BES model and ensures that energy performance gap between simulated and the actual energy use of the building lies within acceptable limits (Raftery et al., 2011). The calibration is an inverse approximation method where the values of inputs are changed until output values are approximately similar to actual energy use (Gucyeter, 2018; Yang and Becerik-Gerber, 2015). Three most commonly used guidelines that define benchmarks for calibration are American Society of Heating, Ventilating, and Air Conditioning Engineers (ASHRAE) Guidelines 14 (2014); Federal Energy Management Program (FEMP)(US-DOE, 2008); and International Performance Measurement and Verification Protocol (IPMVP, 2012). In addition to calibration benchmarks, FEMP has a systematic measurement and verification framework or M&V Guidelines that define four methodologies (Options A, B,C and D) to help in energy conservation projects (Webster et al., 2015). Among the four methodologies Option D, is suitable for assessing energy savings for whole building through calibration process. However, the assessment of energy savings require monitored data before and after application of the EPU's in building. In absence, of complete data only calibration process can be performed.

FEMP M&V Guidelines, Option D and ASHRAE 14 require two calibration benchmarks to be achieved for acceptable BES. If results exceed these limits, the calibrated model becomes invalid and needs to be recalibrated until the error is within permissible limits. These include Mean Bias Error (MBE) (%) and the Coefficient of Variation of Root Mean Square Error (CV(RMSE)) (%). MBE is a non-dimensional bias measure (i.e., sum of errors), between measured and simulated data for each hour. It captures the mean difference between measured and simulated data points and is considered a good indicator of the overall bias in the model. RMSE index assesses data by capturing offsetting errors between measured and simulated data and does not suffer from the cancellation effect that can come in MBE. Cancellation effect occurs where the positive bias compensates the negative bias, and resulting in erroneous validation. Acceptable tolerance limits for the two benchmarks vary according to the type of calibration, hourly or monthly, and are provided in Appendix A, Table A1.

The following steps are involved in performing the calibration process:

- 1) Construction of an initial BES model on HOT2000 based on the engineering drawings, local weather data, occupancy, equipment specifications, and indoor temperatures.
- 2) Adjusting constructed BES model with data obtained from monitoring and making suitable assumptions for unknown parameters.
- 3) Determining MBE and CV(RMSE) values on monthly energy based on results of BES model and actual energy use with Eq. (1-a) and (1-b).

$$MBE (\%) = \frac{\sum_{k=1}^{N_p} (m_k - s_k)}{\sum_{k=1}^{N_p} (m_k)} \quad (1-a)$$

$$CV(RMSE) (\%) = \frac{\sqrt{\sum_{k=1}^{N_p} (m_k - s_k)^2 / N_p}}{\bar{m}} \quad (1-b)$$

Where, m_k and s_k are the respective measured and simulated data points for each model instance 'k'; N_p is the number of data points at interval 'p' (i.e., $N_{monthly} = 12$) and $\bar{m}$ is the average of the measured data points.

- 4) Re-adjustment of the energy model parameters until the results of the benchmark metrics are within acceptable limits of MBE and CV(RMSE) (ASHRAE, 2014; Webster et al., 2015).

Calibrated energy models were tested for variation in energy consumption due to changes in energy upgrades. The energy consumptions under upgrades combinations were used to find the change in the carbon footprint of the house and operational costs.

2.2.2. Life cycle costing and carbon footprint

For this study, the Net Present Value (NPV) method was used to determine the lifecycle cost analysis (LCC) for assessing building upgrades. LCC is an economic evaluation technique that determines the costs of the entire life span of a product or process (Warren, 1994). Typically, LCC for buildings includes construction, maintenance, repair, replacement and disposal costs (McLeod and Fay, 2011; Ruparathna et al., 2017). Previous studies on residential buildings in Canada have considered a 30-year timeline for building operation (Barkokebas et al., 2019; Hesarakı et al., 2019); therefore, the 30-year operational period was considered appropriate for the proposed framework.

In this study relative life cycle cost model by US Federal Energy Management Program (Fuller and Petersen, 1996) was used. Here the $dLCC_t$ is the cost difference between life cycle cost (LCC) for a house with energy upgrades and life cycle cost of a reference case (LCC_r) house. Reference case is a Single-family detached home (SFDH) made according to local code compliance or the status of residential building prior to any upgrades. This cost model does not require costs related to all building components but only the cost differences of the energy components that are being changed (Hamdy et al., 2013; Hasan et al., 2008). Cost differences related to the additional investment, energy bills, maintenance and replacement cost as well as end-of-life cycle costs are considered for $dLCC_t$ calculation as indicated by Eq. (2-b).

$$dLCC_t = LCC_i - LCC_r \quad (\text{CA\$}) \quad (2-a)$$

$$dLCC_t = dC_c + dC_U + dC_{EOL} \quad (\text{CA\$}) \quad (2-b)$$

Where, $dLCC_t$ = difference in total life cycle costs of SFDH with upgrades and base case; LCC_t = total life cycle costs of house with energy upgrades; LCC_r = total life cycle costs of reference house;

t = Study period in years; dC_C = difference in costs of SFDH with upgrades and base case; dC_U = difference in costs in the use stage (operational energy use, maintenance, and replacement costs) of SFDH with upgrades and base case; and dC_{EOL} = difference in costs of the end-of-life of SFDH with upgrades and base case. The end-of-life cycle costs were considered negligible for determining LCC.

Carbon footprint is defined by the total GHG emissions and usually expressed in units of carbon dioxide equivalent (CO₂-eq) (Brander, 2012). Energy-based GHG reduction is dependent on the grid emission factors and the quantity of energy demand reduced through the application of EPU. Grid emission factors are dependent upon the source of energy production and will change with the location of the building (Torcellini et al., 2006). Energy results from the calibrated energy models were used to calculate the long-term GHG impacts of the occupancy profile under the application of EPU. Eq. (3) is used to calculate the GHG emissions associated with energy fuel consumption, where the emission factor changes with the type of fuel.

$$GHG_f = EF_f \times F_f \tag{3}$$

Where, GHG_f is greenhouse gas emission rate of fuel f consumed (kg CO₂-e); EF_f is the emission factor for energy source (natural gas or electricity); while F_f is the annual energy consumed for operating the house equipment and systems.

2.2.3. Ranking upgrade scenarios

The selection of suitable EPU is governed by a number of conflicting parameters that include: energy performance, environmental impacts, economic requirements, regulatory and social aspects (Asadi et al., 2012). The decision-maker has to arrive at a compromise among these parameters when selecting the EPU. Multi-criteria decision-making (MCDM) methods are useful in solving this problem and prioritizing and ranking the most desirable alternatives (Pohekar and Ramachandran, 2004). MCDM is capable of treating qualitative and quantitative criteria and to come up with a ranking of alternatives (El-Jamal et al., 2016).

The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) is one of the most well-established multi-criteria methods that is used to test competing alternatives (Hwang and Yoon, 1981; Kabir et al., 2014). By using the TOPSIS method, the solution nearest to the ideal among competing alternatives is selected. The method has been successfully used in previous studies for selecting the best energy upgrade (Lee and Lin, 2011; Perera et al., 2018; Wang et al., 2017; Zagorskas et al., 2014). Therefore, the TOPSIS method was considered appropriate to meet the goals of this study.

The following steps are involved in performing the TOPSIS method for this particular framework.

- 1) Construction of the decision matrix and weighting matrices. The decision matrix considered 3 criteria: reduction in GHG emissions (kg CO₂-e), initial investment (CA\$) and payback period (Years). Weighting matrix is generated by defining five weighting schemes (Table 1) representative of investors'

preference for pro-environmental or pro-economic investments. In pro-environmental option, more weight is given to the reduction of GHG emissions while for a pro-economic option lowest PBT and Initial capital cost (IC) are given maximum weight.

- 2) Normalization of the decision matrix through the conversion of different criteria into non-dimensional values using Eq. (4).

$$\bar{z}_{ij} = z_{ij} / \sqrt{\sum_{i=1}^j z_{ij}^2}; \cdot i = \overline{1, n} \cdot j = \overline{1, m} \tag{4}$$

Where, “ z_{ij} ” is an entry in the decision matrix and m represents the total number of rows and n represents the total number of columns.

- 3) Generation of the weighted matrix through multiplication of weights of each criterion with entries in normalized matrix.
- 4) Determination of the best and worst alternatives for each criterion.

The best solutions (V_b^+) for the weighted normalized matrix are selected out of all alternatives:

$$V_b^+ = [\text{Max}_{GHG}, \text{Min}_{IC}, \text{Min}_{PBT},]$$

The worst solutions (V_b^-) for the weighted normalized matrix are selected out of all alternatives:

$$V_b^- = [\text{Min}_{GHG}, \text{Max}_{IC}, \text{Max}_{PBT},]$$

- 5) Calculation of distance from ideal solution using Euclidean distance.

The distance of alternative from the positive ideal was found by using Eq. (5-a) and for negative ideal using Eq. (5-b).

$$d_i^+ = \sqrt{\sum_{j=1}^m \left(v_{ij} - V_b^+ \right)^2} \tag{5-a}$$

$$d_i^- = \sqrt{\sum_{j=1}^m \left(v_{ij} - V_b^- \right)^2} \tag{5-b}$$

The relative closeness to the ideal solution was found by Eq. (5-c)

$$CL_i^* = d_i^- / d_i^- + d_i^+ \tag{5-c}$$

- 6) Ranking the alternatives based on relative closeness to the ideal solution.

Table 1
Criteria weights for different occupant preferences.

Selection Criteria	Weights of Criteria under different preference scenarios				
	Pro-Environmental	Higher weightage for environment	Equal importance	Higher weightage for economy	Pro-Economic
GHG emission reduction (kg CO ₂ -e)	1	2/3	1/2	1/3	0
Capital Investment (IC)	0	1/6	1/4	1/3	1/2
Payback Period (PBT)	0	1/6	1/4	1/3	1/2

3. Framework implementation

3.1. Study area

A case study approach is taken to apply and demonstrate the framework using field data obtained from two living laboratory houses located in the Kelowna city, Okanagan Valley (Canada). Although other living laboratories are present in Canada including the Canadian Center for Housing Technology (CCHT) houses in Ottawa (CCTH, 2016) and the Architype houses near Toronto (STEP, 2011), these living labs are the first of their kind in Canada conforming to Okanagan region construction practices.

The two houses are located in one of the fastest growing areas in Canada, the Okanagan Valley. The case study homes were constructed in 2016 and occupied in 2017. These mid-size residences are identical in their architectural design, location, and orientation and are exposed to same external features. However, the two homes vary with respect to the building envelope, heating and cooling systems, and occupancies. The household characteristics for the homes are provided in Table 2. The construction materials and thermal characteristics obtained from the industrial partners were used to develop the energy model. The geometry and other relevant information of these houses was extracted from the relevant drawings and bills of quantities. The thermal characteristics of specific envelope components and equipment such as HVAC, lighting, and appliances were collected from the manufacturers' specifications.

Architectural plans for the homes were identical and represented by in Fig. 2. The case study homes cover an area of 291.25 m² and consist of two storeys, a main floor and a basement that is partially underground. One house called Standard Home (STH) is built by following the BC building code 2012 (The Government of British Columbia, 2020); the house represents typical construction practices in Okanagan Valley and is base case scenario for this study. The other home called Advance Tech Home (ATH) is representative of an energy-efficient home and is constructed with the

most energy-efficient materials and systems locally available in Kelowna (Okanagan Valley). In addition to having higher fabric insulation (higher insulation and foundation made of insulated concrete forms- ICF blocks), better performance windows (Vinyl triple glazed windows c/w 366 Low-E), an HVAC system consisting of a geothermal heat source pump and energy star rated appliances, the ATH is supplied with renewable energy from a solar (PV) system installed on the roof.

The two houses represent occupancy profiles most common in Canada: (a) a family with dependent children where the parents work full time; and (b) a retired couple who spend most of their time indoors. The two profiles are representative of 52.3% of Canadian private household structures with couples with children (Occupancy Profile 1 for this study) representing 26.5% and couples without children (Occupancy Profile 2 for this study) representing 25.8% (Statcan, 2017). Canada does not have a mandatory retirement age, though average age of retirement for most Canadians is 63.5 years (Statistics Canada, 2020). Since it was known that the residents pertaining to Occupancy Profile 2 are retired, the profile is called retired couple for this study.

The STH model has previously been used in the study by Perera et al. (2018) for assessing household and transport incentives for clean energy. This study extends the original model by calibration and considering additional EPU's. The detailed monitoring ensures more realistic representation of occupants behavior and savings from energy upgrades. In order to make a comparison between the influence of two occupancy profiles on energy and GHG reduction potential of various EPSS, STH was upgraded with energy upgrades present for ATH while ATH was downgraded with the standard materials, equipment and appliances present in STH.

3.2. Energy monitoring

An intrusive load monitoring method was employed for determining the energy use by various building components. The living

Table 2
Household characteristics.

Parameter	Standard Home (STH)	Advance Tech Home (ATH)
Occupancy Profile	 2 working adults (aged 35–49) 2 teenagers (aged 15–19)	 Retired couple (aged 50–64)
Total area of building (m ²)	291.25	291.25
Gross floor area (m ²)	249.91	249.91
Area of walls (m ²)	364.57	364.57
Area of doors (m ²)	6.60	6.60
Area of windows (m ²)	57.91	57.91
Space cooling and heating (HVAC)	Payne (PG92SCS) 17.58 kWh AFUE 92.1% Natural Gas & Payne (PA14NC) 9.96 kWh 14 SEER Split A/C	5 series (500A11) – Geothermal c/w ECM variable speed blower (Heating 4 COP, Cooling 5.6 COP) GeoSpring™ hybrid electric water heater, 303 L, EF 3.14, Electricity-based
Domestic hot water (DHW)	Standard DHW system, 227 L, EF 1.901, Electricity-based	9.525 mm EPS Styrofoam & USI-0.28 Batt (Eff. USI 0.27)
Wall-Insulation (WL)	USI 0.28 Batt (Eff. USI 0.32)	USI 0.28 Batt, USI 0.11 blown (Eff. USI 0.09)
Celling- Insulation (RF)	USI 0.26 Batt, USI 0.14 blown (Eff. USI 0.14)	ICF blocks (Eff. USI 0.25)
Foundation (FN)	USI 0.26 Batt (Eff. USI 0.32)	Vinyl triple glazed windows c/w 366 low-E
Windows (WN)	Vinyl double glazed windows c/w 180 low-E	Energy-Star Rated Appliances:
Appliances (APP)	Standard Appliances: Dishwasher, washer & dryer, fridge, oven and hood fan	Hood fan with LED lighting and ultra-quiet blower, dishwasher, heat pump dryer and washer, 5 door fridge, double ovens
Lighting (LED)	Incandescent bulbs	LED bulbs
Solar (PV)	None	10 panels (16.3 m ²) azimuth 15° and slope 25°

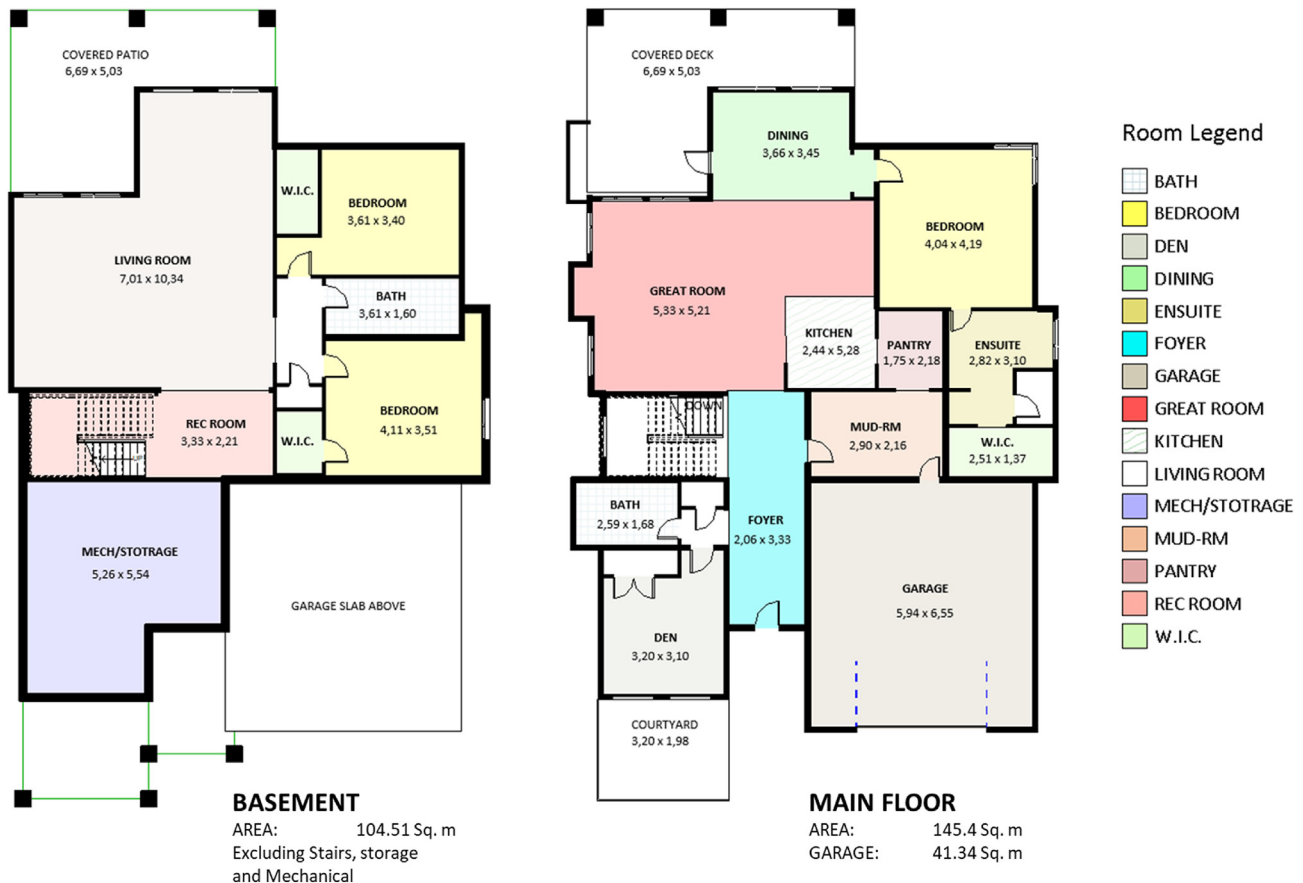


Fig. 2. Floor plans of case study homes.

laboratory was installed with temperature, humidity sensors as well as with electricity and natural gas consumption monitors. The system architecture of the data monitoring and acquisition system is shown in Fig. 3. The real-time data was captured for one-year, and a comprehensive database was developed for evidence-based research.

Fig. 4 shows the energy use pattern for the HVAC systems, minor appliances (including small kitchen appliances such as toaster oven, microwave oven, electric kettle), lighting, domestic hot water (DHW) system, laundry washer, and dryer in two homes. It is observed that the energy used in appliances by the ATH is more despite being more efficient appliances. The presence of a ground source heat pump also indicates a higher use of energy during summer months as compared to a conventional HVAC system. The current research assesses monthly energy use of different systems using average temperature and humidity levels; while daily, weekly and seasonal variation in energy use are not part of this research.

3.3. Energy modelling

The BC Building Code-2012 and local municipality by-laws were used while designing the base-case models of the two buildings. The energy models for the two homes were generated based on the detailed drawings, local metrological data (Fig. 5.) and suitable assumptions regarding operation of different appliances and systems. The energy models were constructed using HOT2000 version 11.7b23 (NRCAN, 2020a). HOT2000 uses long term weather data in bin method and steady-state models for assessing monthly energy loads (Mohazabieh, S.Z. Ghajarkhosravi and Fung, 2015). HOT2000

is used extensively for design and certification of low-rise residential buildings in Canada (NRCAN, 2020a).

In order to determine the error in the base case models the monthly energy results of the simulation and monitored energy were compared using MBE and CV(RMSE) metrics (ASHRAE, 2014; Webster et al., 2015). Studies have shown that small errors in simulated and measured energy use are due to the simplification done by tools to perform simulation, while larger errors are due to incorrect model inputs (Clarke et al., 1993). Initial base models generated large errors between the actual and simulated energy uses. Manual calibration was performed to decrease these discrepancies in the energy results. Manual calibration of energy models has been used by the majority of researchers and involves iterative adjustments until the model is validated for the specified standard (Coakley et al., 2014). Multiple trials were done by upgrading the model with field measurements until acceptable errors were obtained. The final calibrated base case models had MBE and CV (RMSE) respectively to be 0.99 and 3.46 for STH and -0.06 and 0.88 for ATH (Table 3). It was possible to obtain low errors due to the detailed energy, temperatures and humidity data collected through the intrusive load monitoring technique. The operation parameters for the calibrated models are provided in Table 4.

The calibrated models were then run for different EPU combinations to determine the variation in annual energy use. A total of 514 simulation runs were performed on the nine EPU options (present in Table 2). In order to increase the simulation time interaction impact between EPUs combinations was assumed to be negligible. The operational energy consumptions obtained from the

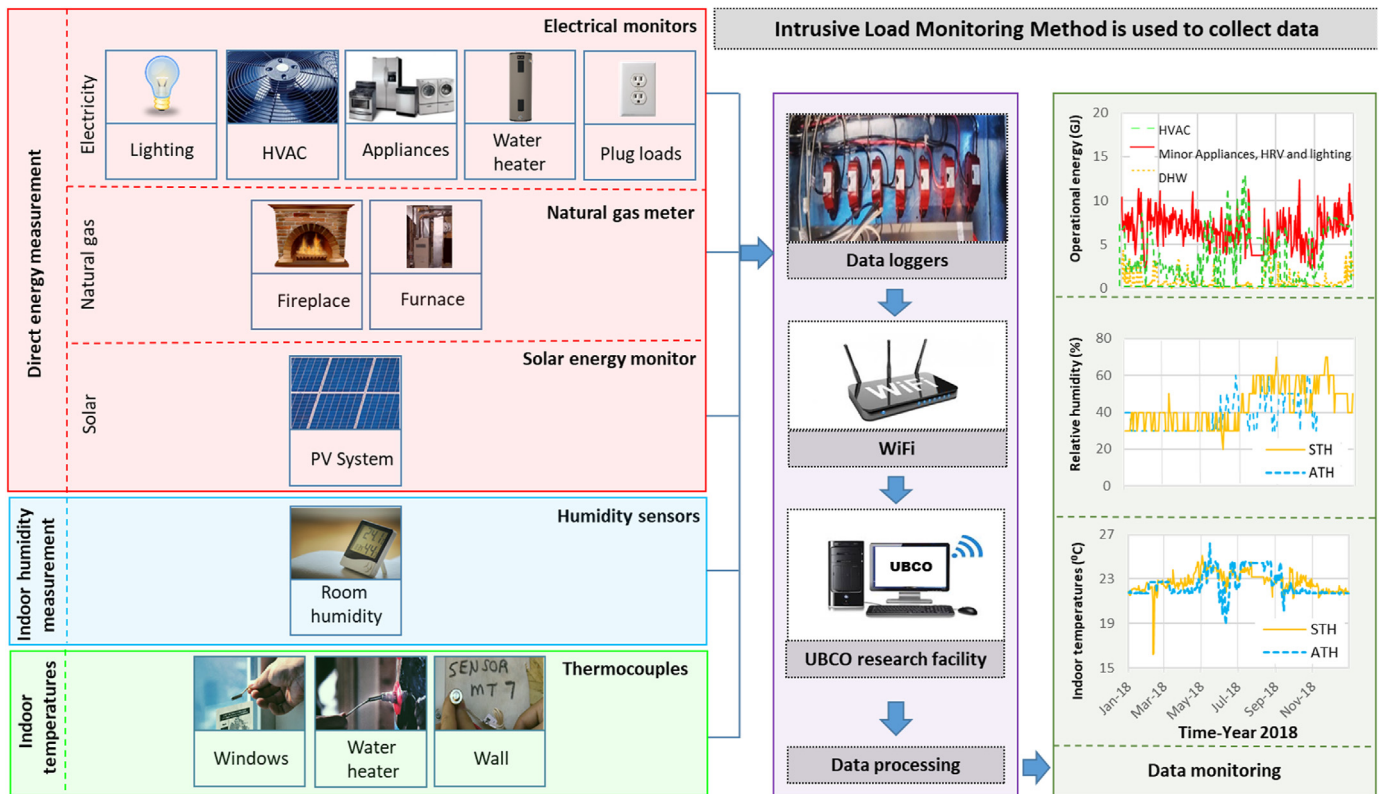


Fig. 3. System architecture for the Living Lab.

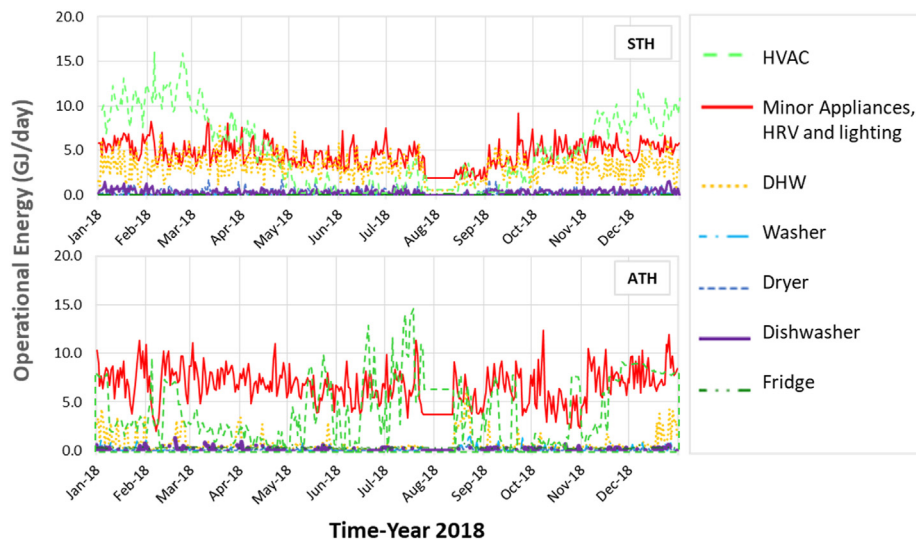


Fig. 4. Trend of measured energy use in STH (top) and ATH (bottom) graph.

aforementioned models upgraded with EPU were used in the next phases to quantify the GHG emissions, operational costs, and life cycle costs. It should be noted that the comparison between the validated models for the two profiles was not possible based on the calibrated models due to the difference in materials, equipment, and appliances of the two homes. In order to compare the impact of energy upgrades for the two homes with respect to two occupancy profiles, the EPU were added in STH while energy systems, equipment, and appliances in ATH were downgraded with those present in ATH to find the annual operational energy, GHG

emissions and LCC. Hence, it was possible to obtain the impact of occupancy profiles for same energy systems, equipment and appliances.

3.4. Life cycle costing and carbon footprint

The initial construction cost of the SFDH base case was estimated using RSMeans residential cost database (RS Means Company, 2016), market prices of appliances, ASHRAE report on the economic database for green residential buildings (ASHRAE,

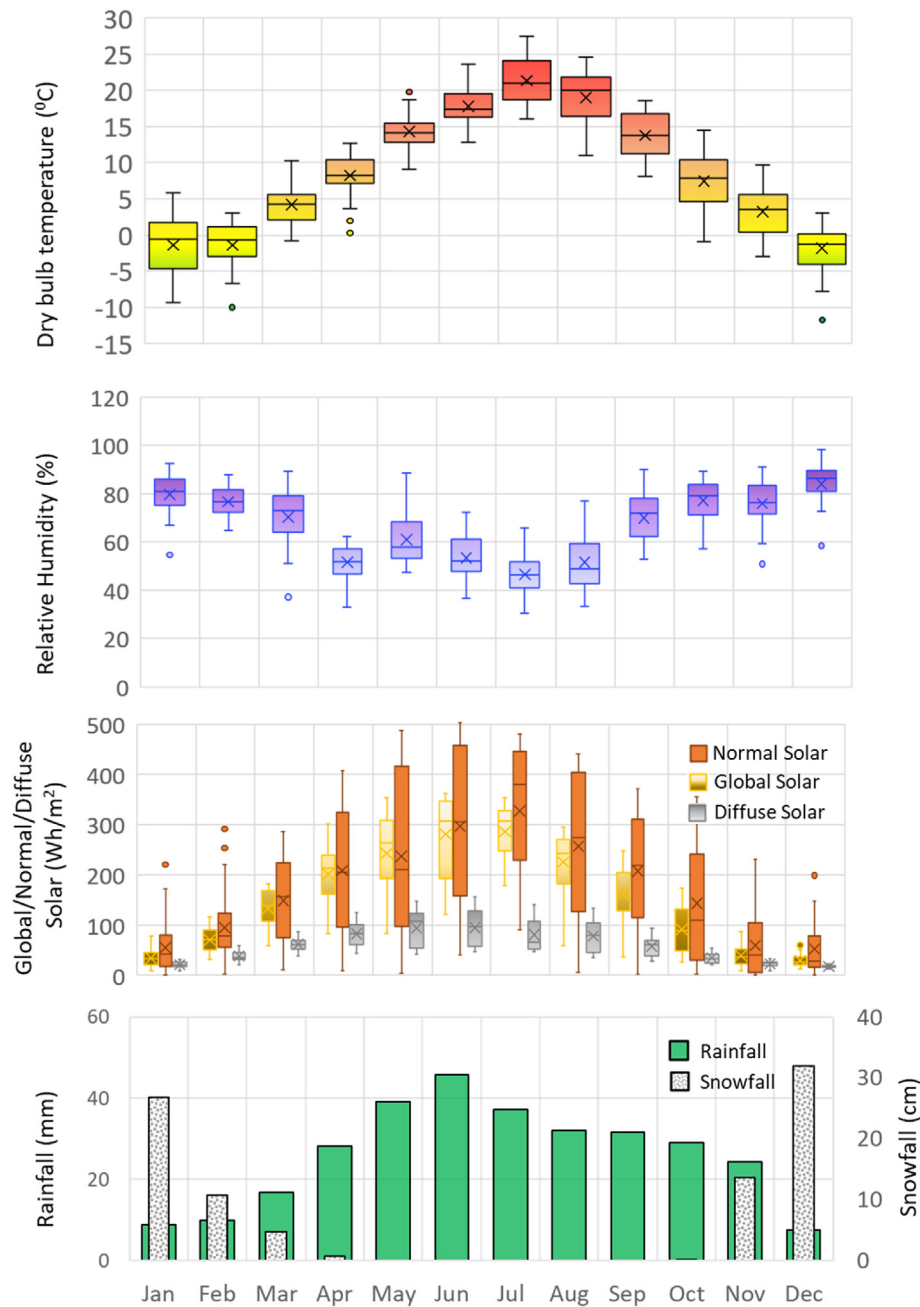


Fig. 5. Local annual weather conditions in Kelowna.

Source(Climate OneBuilding, 2020; Environment Canada, 2020):

Table 3
MBE and CV(RMSE) analysis for monthly energy consumption.

House	MBE (%) ^a	CV (RMSE) (%) ^b
Standard Home (STH)	+0.99	3.46
Advance Tech Home (ATH)	- 0.06	0.88

^a Acceptance limits: MBE (monthly) $\leq +5\%$ (ASHRAE, 2014; Webster et al., 2015).

^b Acceptance limits: CV (RMSE) (monthly) $\leq +15\%$ (ASHRAE, 2014; Webster et al., 2015).

2009), and data obtained from the Okanagan developers (Authentech Homes, 2016). The costs obtained from RSMeans and the consultation process were adjusted to give a reasonable estimate of the Kelowna construction costs. The costs of construction

were limited to additional investments for building energy upgrades. Costs relating to home insurance, landscaping, furniture, mortgage payment, government incentives for green upgrades were not considered. Table 5 shows the costs associated with different energy upgrades.

The maintenance period for different building systems is used as defined by Kirk et al. (1995) which varies with different upgrades. Moreover, costs due to the replacement of existing systems, pollution damage and hazard prevention at the rehabilitation process were not considered for this study. Various economic parameters considered for cost analysis are provided in Table 6. The discount rate of 3% and an inflation rate of 5% were assumed based on the literature (IMF, 2016; Snodgrass, 2003). The energy costs for the house were calculated using the electricity and natural gas tariff

Table 4
Operation parameters for the calibrated models.

Operation parameters	Standard Home (STH)	Advance Tech Home (ATH)
T _{heating} (°C)	21	21
T _{cooling} (°C)	22.64	22.64
Occupancy Time (% of day at home)	50	50
Electrical Appliances (kWh/day)	11.6	18.65
Lighting (kWh/day)	2.6	0.6
Hot Water Temperature (°C)	55.56	46.67

Table 5
Energy upgrades and associated costs.

No.	Energy upgrades	Abbreviation	Type of energy upgrades	Expected service life (Years)	Annual Maintenance as percentage of capital cost (%)	Initial cost difference CA\$(US\$)	Cost of maintenance and replacement (30- year) CA\$(US\$)
1	Appliances ^a	APP	Active	16.5	5	3000 (2130)	6185 (4391)
2	Domestic hot water	DHW	Active	15	5	1200 (852)	2474 (1757)
3	Foundation-ICF	FN	Passive	30+	— ^c	10,000 (7100)	0 ^c
4	Space cooling and heating ^b	HVAC	Active & Renewable	15	5	9000 (6390)	18,555 (13,174)
5	Lighting	LED	Active	15	3	43 (31)	47 (33)
6	Solar	PV	Renewable	25	1.5	8600 (6106)	7180 (5098)
7	Roof- Insulation	RF	Passive	30+	— ^c	300 (213)	0 ^c
8	Wall-Insulation	WL	Passive	30+	— ^c	1000 (710)	0 ^c
9	Windows	WN	Passive	40	2.8	12,127 (8610)	6770 (4807)

^a Appliances include kitchen (dishwasher, exhaust hood, stove and oven) and laundry appliances (dryer and clothes washer).

^b HVAC systems upgrade was considered to be ground source heat pump that serves part of both heating and cooling systems of the house and involves use of electricity for running pumps and renewable energy.

^c Maintenance and replacement of Wall-insulation, Ceiling insulation and ICF foundation is beyond the study period of 30-year.

Table 6
Economic parameters.

Parameter	Value
Discount rate	3% ^a
Inflation rate	5% ^a
Life Period	30-year ^b
Cost of Electricity	9.845 CA¢/kWh (7.1 US¢/kWh) ≤ 1600 kWh/month ^c and 15.198 CA ¢/kWh (10.90 US¢/kWh) > 1600 kWh month ^c
Cost of Natural Gas	1.141 CA\$/GJ ^d (0.81 US\$/GJ)

^a Discount and inflation rates are in accordance with (International Monetary Fund, 2016; Snodgrass, 2003).

^b Life period of 30-year is adopted in accordance with amortization period for Canadian homes (CMHC, 2019)

^c Electricity tier rates based on FortisBC rates (FortisBC, 2017).

^d Natural gas rates based on FortisBC rates (FortisBC, 2017).

defined by the local utility providers. Accordingly, the cost of electricity was assumed as 9.845CA¢/kWh (7.1US¢/kWh) for the consumption up to 1600 kWh and 15.198 CA¢/kWh (10.90 US¢/kWh) for the consumption above 1600 kWh. The cost of natural gas was assumed as 1.141 CA\$/GJ (0.82 US\$/GJ) (FortisBC, 2017). Additional charges related to electricity and natural gas supply such as customer charge, basic daily charge, delivery charge, storage and fuel transportation charges were also considered in calculation of operational energy in the building life cycle. The details related to natural gas and electricity rates are provided in Appendix A, Tables A2 and A3.

Total GHG emissions of a residential building depend on the supply energy mix and the energy consumption of the residential activities. In Canada, the emission factors vary with the primary energy sources (Kikuchi et al., 2009). Unlike other provinces in Canada, BC has a low-emission electricity supply since the major portion of the grid electricity is hydro-based (NEB, 2018). Electricity emission factor is 2.80 kgCO₂-eq./GJ whereas the emission factor of natural gas is 65.75 kgCO₂-eq./GJ (BC Ministry of Environment, 2014).

4. Results and discussion

The above-described framework was used to assess the variation in annual operational energy, GHG emissions and life cycle costs associated with the application of EPU in a single-family detached house under two different occupancy profiles. Since the operational life cycle period of 30-year was considered according to generic amortization period for residential buildings (CMHC, 2019), only EPU that had PBT of 30-year or less were considered for comparison and ranking. The EPU were then ranked with respect to five scenarios representing the priority of the investor. The results of the application of the framework for the two residential occupancies are presented in this section.

4.1. Occupancy profile 1

Occupancy Profile 1 comprised of four family members including two working adults and 2 school-going children. EPU that fulfilled the PBT limit of 30-year or less with respect to the energy savings (<https://www.sciencedirect-com.ezproxy.library>).

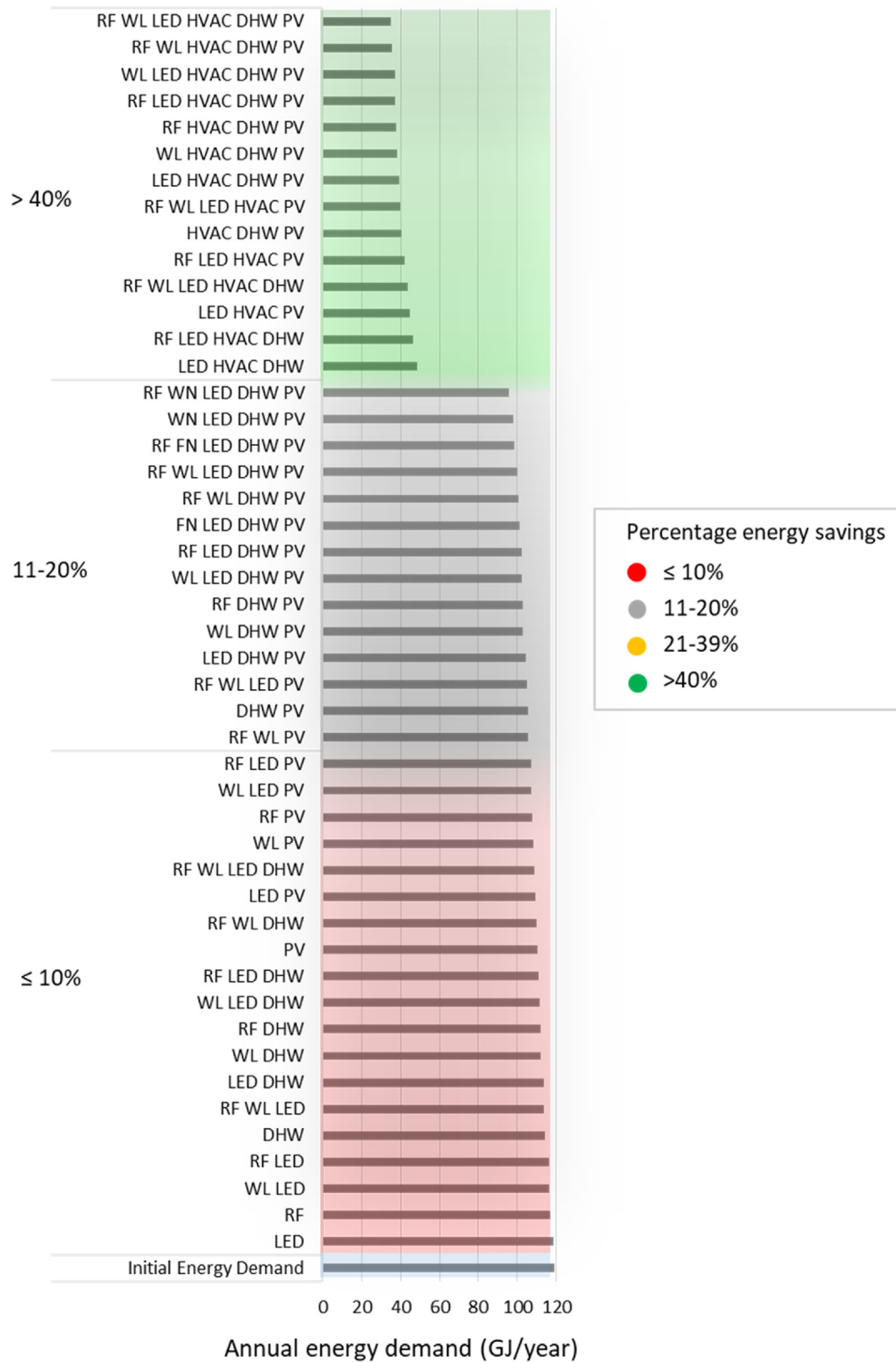


Fig. 6. Reduction in annual energy demand (GJ) with energy upgrades for tested Occupancy Profile 1.

[ubc.ca/science/article/pii/S0959652619344336](https://www.sciencedirect.com/science/article/pii/S0959652619344336), Appendix B, Supplementary data), GHG emissions reduction and PBT are discussed in this section.

4.1.1. Annual operational energy

Fig. 6 depicts the energy savings possible with respect to the selected upgrades for Occupancy Profile 1. These EPU have been distributed into four groups with respect to percentage energy savings to the initial energy use (119.33 GJ/year) of the Occupancy Profile 1. The majority of the EPUs with PBT of 30-year provide energy savings in the range 0–20%. As expected, the upgrades yield more savings in combinations and only four upgrades LED, RF, DHW, and PV give reasonable savings. From the chart, it can be seen that by far the greatest energy savings are up to 71% for the combination “RF WL LED HVAC DHW PV”. Among the passive energy upgrades, wall (WL) and roof (RF) insulations yielded savings in the majority of the combinations, while among the active systems, domestic hot water (DHW) was determined to have high-energy benefits. HVAC energy upgrade yielded more than 50% in operational energy savings; however, the system had a high initial cost that increased its PBT (beyond 30-year) and made this upgrade financially unfeasible.

4.1.2. Payback period and carbon footprint

Fig. 7 shows the relationship between the extra initial expenditure and PBT and reduction in GHG for the 47 shortlisted energy upgrades. Three main clusters of energy upgrades associated with initial expenditure and PBT can be clearly identified from this figure. It was observed that for investments below CA\$ 5,000, the PBT are all less than 15 years. This kind of investment will be suitable for most owner-occupants since the average tenure calculated for homeowners in North America is 8-year (Hansen, 1998). The cluster in the middle shows options of energy upgrades when the extra expenditure ranges between CA\$ 8,600 to 12,000. It was observed that some of the energy upgrades that have the potential for decreasing GHG emissions beyond kgCO₂-eq have a high PBT of up to 30-years. The energy upgrades were also seen to offer more GHG reduction in combinations as compared to

individual upgrade; for instance, energy upgrade combination “RF WL LED HVAC DHW” provides about 200% more GHG reduction than PV systems alone. For the investment between CA\$ 17,000 to 22,000, the majority of the energy combinations provide high reductions in GHG emissions. Since the budget required for these upgrades is high, financial help in the form of financial incentives from the government or utility providers would be needed to make these energy upgrades desirable for the users.

4.1.3. TOPSIS results

In order to rank the energy upgrade for each profile decision matrix composed of initial cost investment, the PBT and GHG emissions were constructed. Fig. 8 and Table 7 show results of the first ten highest ranked energy upgrades. It is seen for among the given scenarios the choices for pro-economic scenario shows highest variation in GHG emission reduction, IC and PBT. According to Table 7, as the decision-maker preference changes from pro-environment towards pro-economic, lesser energy upgrades are used. Roof insulation (RF), wall insulation (WL), lighting upgrade (LED) and upgrade of the domestic hot water system (DHW) are the only upgrades that were found in the list of top ten energy upgrades for the five user preferences. It is interesting to note that for a family of four, the DHW forms part of EPUs combinations under all scenarios. Water heating in Canadian homes accounts for 20% of the energy consumed and also accounts for a large portion of residential carbon footprint (Amirirad et al., 2018). A family of four is likely to spend more hot water in showering and bathing; hence are able to get more benefits by using a more efficient water heating system.

Table 7 also shows that the upgraded HVAC system forms part of the majority of the EPU combinations. The upgraded HVAC has a ground source heat pump and is known to bring a number of technical, environmental and socio-economic benefits (Karytsas and Chorapanitis, 2017); however, the initial investments for this system are high and show a long PBT unless some external financial incentives are present. Hence it is not surprising that this upgrade did not form part of the top ten pro-economic choices. Contrary to the HVAC upgrade, the LED is a very cost-effective EPU and forms

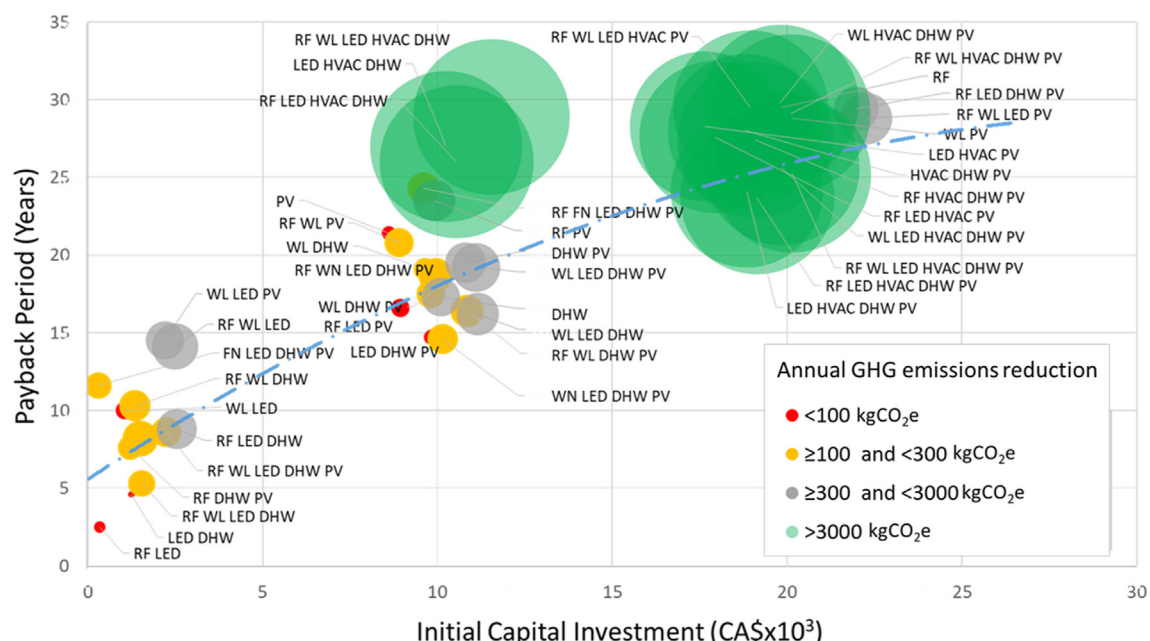


Fig. 7. Bubble chart for Occupancy Profile 1 with details of IC, PBT and GHG emission reduction associated with energy upgrades.

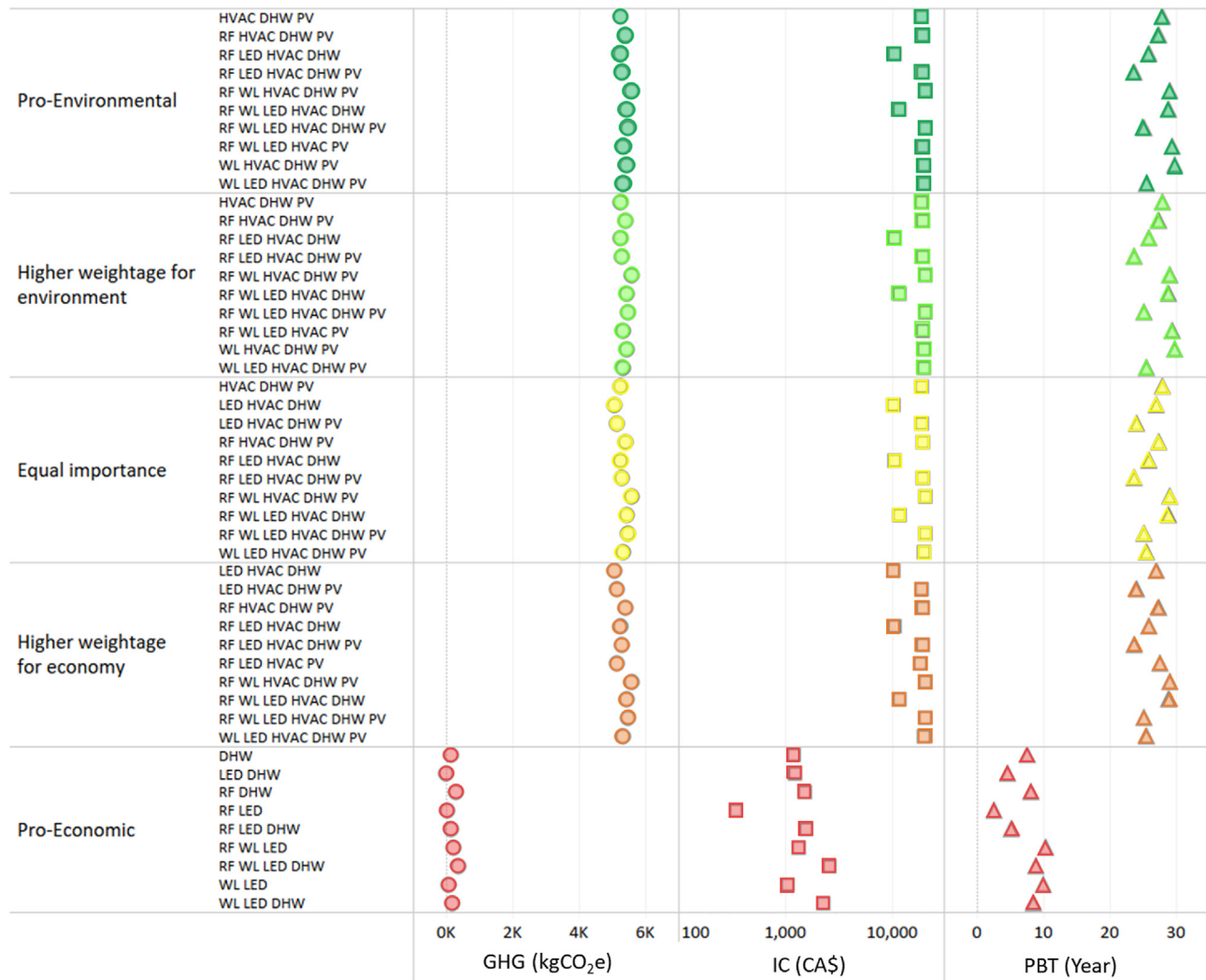


Fig. 8. Comparison between different scenarios- Occupancy Profile 1.

Table 7

Occupancy Profile 1: Ranking for energy upgrade for decision maker preferences.

Pro-Environment		User-defined			Pro-Economic
Ranking	Scenario-1	Scenario-2	Scenario-3	Scenario-4	Scenario-5
1	RF WL HVAC DHW PV	RF WL LED HVAC DHW	RF LED HVAC DHW	RF LED HVAC DHW	LED
2	RF WL LED HVAC DHW PV	RF WL LED HVAC DHW PV	RF WL LED HVAC DHW	LED HVAC DHW	RF LED
3	WL HVAC DHW PV	RF LED HVAC DHW	RF LED HVAC DHW PV	RF WL LED HVAC DHW	LED DHW
4	RF WL LED HVAC DHW	RF LED HVAC DHW PV	RF WL LED HVAC DHW PV	RF LED HVAC DHW PV	RF LED DHW
5	RF HVAC DHW PV	RF WL HVAC DHW PV	LED HVAC DHW	RF WL LED HVAC DHW PV	DHW
6	RF WL LED HVAC PV	RF HVAC DHW PV	WL LED HVAC DHW PV	LED HVAC DHW PV	RF DHW
7	WL LED HVAC DHW PV	WL LED HVAC DHW PV	LED HVAC DHW PV	WL LED HVAC DHW PV	WL LED DHW
8	RF LED HVAC DHW PV	WL HVAC DHW PV	RF HVAC DHW PV	RF HVAC DHW PV	RF WL LED DHW
9	HVAC DHW PV	RF WL LED HVAC PV	RF WL HVAC DHW PV	RF WL HVAC DHW PV	WL LED
10	RF LED HVAC DHW	HVAC DHW PV	HVAC DHW PV	RF LED HVAC PV	RF WL LED

part of a suitable energy upgrade choice. Solar photovoltaic (PV) system installation is another renewable option that was tested for case studies. Though the costs of PV system have decreased substantially over the past decade the PV was not part of scenario-5 choice. However, the electricity costs are rising over the past

decade; for instance, electricity rates in Ontario (Canada) have risen by 7.7% (McKittrick and Elmira, 2017). This implies that the use of PV upgrades may soon become a pro-economic in addition to pro-environment choice. In addition, three energy upgrades that did not form part of top-ranked combinations in any of the five

preference scenarios were windows (WN), ICF foundation wall (FN) and appliances (APP). All these options required large expenditure and the associated GHG reduction were not significant to form part of the top pro-environment related choices. Hence, for a typical family of four, the energy upgrades that need to be emphasized are DHW, HVAC, LED, PV, WL and RF.

4.2. Occupancy profile 2

Occupancy Profile 2 comprised of a retired couple who spend most of their time at home. In this section, EPU that fulfilled the PBT limit of 30-year or less are discussed with respect to the energy savings (<https://www.sciencedirect.com.ezproxy.library.ubc.ca/science/article/pii/S0959652619344336>, Appendix B, Supplementary data), GHG emission reduction and PBT.

4.2.1. Annual operational energy

Fig. 9 depicts the energy savings possible with respect to the selected upgrades for Occupancy Profile 2. Similar to energy savings groups made for occupancy the selected EPUs were grouped into four categories based on their energy saving potential with respect to a base case annual energy 105.62 GJ/yr. It can be seen from Fig. 9 that the filtered EPUs for the retired couple give significantly more savings for similar EPUs than those for Occupancy Profile 1 EPUs. The majority of EPU give energy savings in the range of 21–39%. The highest savings of 71% are observed for the combination “WL LED HVAC DHW PV”. Similar to Occupancy Profile 1, WL and RF insulations yielded the highest savings among the passive systems, and DHW gave savings among the active systems.

4.2.2. Payback period and carbon footprint

Occupancy Profile 2 is depicted in energy use under different energy upgrades for the stay at home retired couple. The initial costs, PBT and GHG emissions for feasible energy upgrade options for Occupancy Profile 2 are shown in Fig. 10. Similar to Occupancy Profile 1, energy upgrades can be seen as clusters between expenditure and PBT. However, a clear contrast between the two profiles is a very low GHG reduction (less than 100 kgCO₂-eq) associated with the majority of the upgrades. Hence, it is indicated that the energy use by Occupancy Profile 2 is significantly different from Occupancy Profile 1 and offers few options to reach the same level of GHG reduction targets. Highest reduction potential for Occupancy Profile 2 for the case study was found for the combination “RF WL LED HVAC DHW PV”. It is observed that for this profile higher investment of up to CA\$ 11,000 is not significantly decreasing GHG emissions. Therefore, for Occupancy Profile 2 in order to achieve high reduction targets needed to achieve sustainable buildings will require external help from the government and other organizations. This is significant since the majority of the studies have shown senior residents often own bigger houses and usually have a low-income source (Yohanis et al., 2008).

4.2.3. TOPSIS results

Table 8 shows ranking for the top ten upgrade choices for the house with the retired couple defined by Occupancy Profile 2. Similar to the trends shown for Occupancy Profile 1, more energy upgrades are needed for a greater reduction in GHG emissions. It is seen that single EPUs form part of highest ranked EPUs for Occupancy Profile 2. It is noted from Fig. 11 that the shortlisted upgrades do not achieve the same level of GHG mitigation as achieved for Occupancy Profile 1 EPUs in Fig. 8.

Interestingly, the WN upgrade forms part of the top ten choices of energy upgrades. These findings imply that a larger expenditure is needed for achieving meaningful GHG reduction. Some studies have also shown that the older occupants belong to the low-income

group. Therefore increased energy use accompanied by higher initial investment and longer PBT needs to be addressed by utilities and government. Some utilities in Canada are already offering incentives for increasing the energy efficiency of homes occupied by senior citizens. However, more extensive and tailored incentives for this age group are still needed.

4.3. Discussion

The above results demonstrate the suitability of different EPUs with respect to occupancy profile and investor's priority. It is observed that low-cost energy upgrades have a higher potential for energy savings for Occupancy Profile 2. However, combinations of high-cost EPUs provide greater energy saving and GHG emission reduction potential for Occupancy Profile 1 as compared to Occupancy Profile 2. This finding validates simulated results found by Motuziene and Vilutiene (2013) who observed higher savings for houses with four occupants compared to working and retired couple profiles. This higher energy savings for Occupancy Profile 1 can be attributed to a higher number of occupants. De Meester et al. (2013) work on different occupancy profiles also showed that as a house becomes more efficient the internal heat gains from occupants play an important role in decreasing heating energy demand. Higher savings are observed for Occupancy Profile 1 since space heating is still the predominant end use energy (64%) in residential buildings of Canada (NRCAN, 2019b).

Among EPUs, wall and roof insulations were suitable low-cost options and formed part of a number of combinations with PBT of 30-year (Figs. 7 and 10). Studies agree that the improvement of building envelopes through higher insulation is a useful energy reduction strategy. Marshall et al. (2016) investigated the impacts of occupancy profiles on the UK households through BES based on literature. In contrast, the results of this research are drawn from field data and provide insights on selecting EPUs for Canadian households which can be extended to other similar locations and population groups.

In current framework, one-year monitored data was used for calibrating the energy models. In the absence of monitored data, energy models can be calibrated using house characteristics, annual data on monthly utility bills coupled with a questionnaire survey for more accuracy. When only utility data is used for calibration at least three-year monthly utility data is recommended to be used to ensure average energy use per month is correct (Hubler et al., 2010). The results of calibration from either monitored data or utility bills can be reasonably representative of the occupancy profile energy use. However, model generated using utility data is unable to predict performance accuracy for individual systems and equipment. It is therefore recommended to assess the occupant behavior, occupancy times on weekdays and weekends, indoor temperature settings in order to remove possible errors. Hence, the proposed framework can be modified to include energy models calibrated through a survey of occupants and the monthly energy bills to determine suitable EPUs.

4.3.1. Investor preference

This study did not find a significant difference between the energy upgrade for the pro-economic preference for the two profiles. However, changes in both ranking order and the type and number of energy upgrades vary with the pro-environment preference. This finding has important implications for developing tailored energy audit and energy saving incentives programs. Currently, energy audit and energy saving incentives programs by government and utility providers are designed on the basis that cost-effectiveness is the sole criteria for EPU selection (Ingle et al., 2014). Since a visible difference is present between the ranking of

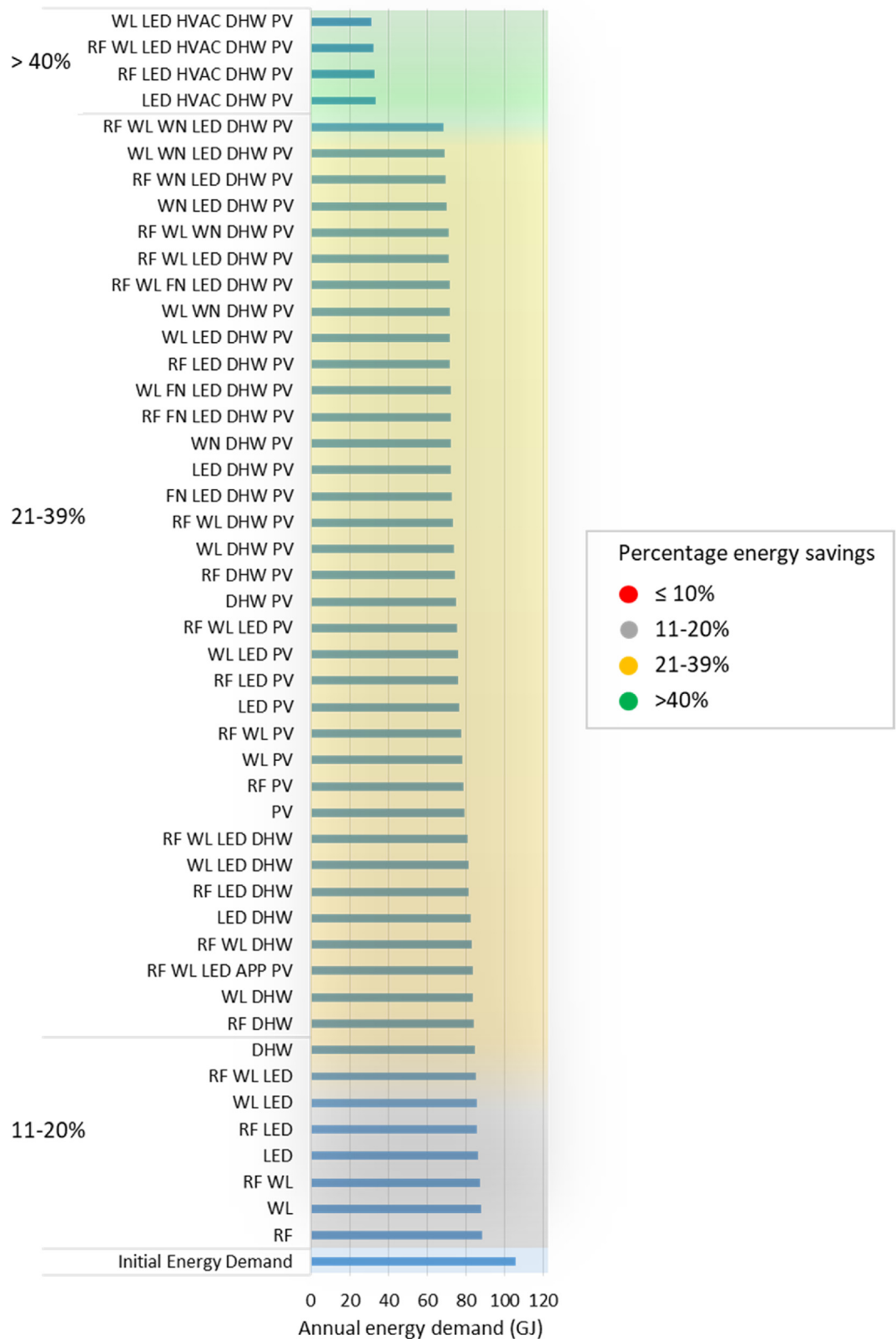


Fig. 9. Reduction in annual energy demand (GJ) with energy upgrades for tested Occupancy Profile 2.

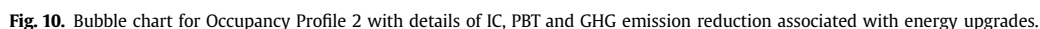


Table 8

The findings of this study are restricted to two occupancy profiles that represent only 52.3% of the Canadian private households. According to Statistics Canada (2017), private households are divided into 7 occupancy profiles: (1) Couples with children (Occupancy Profile 1 for this study) (26.5%), (2) Couples without children (Occupancy Profile 2 for this study) (25.8%), (3) Lone parents (8.9%) (4) Multi-generational households (2.9%), (5) One-person households (28.2%), (6) Households with two or more persons

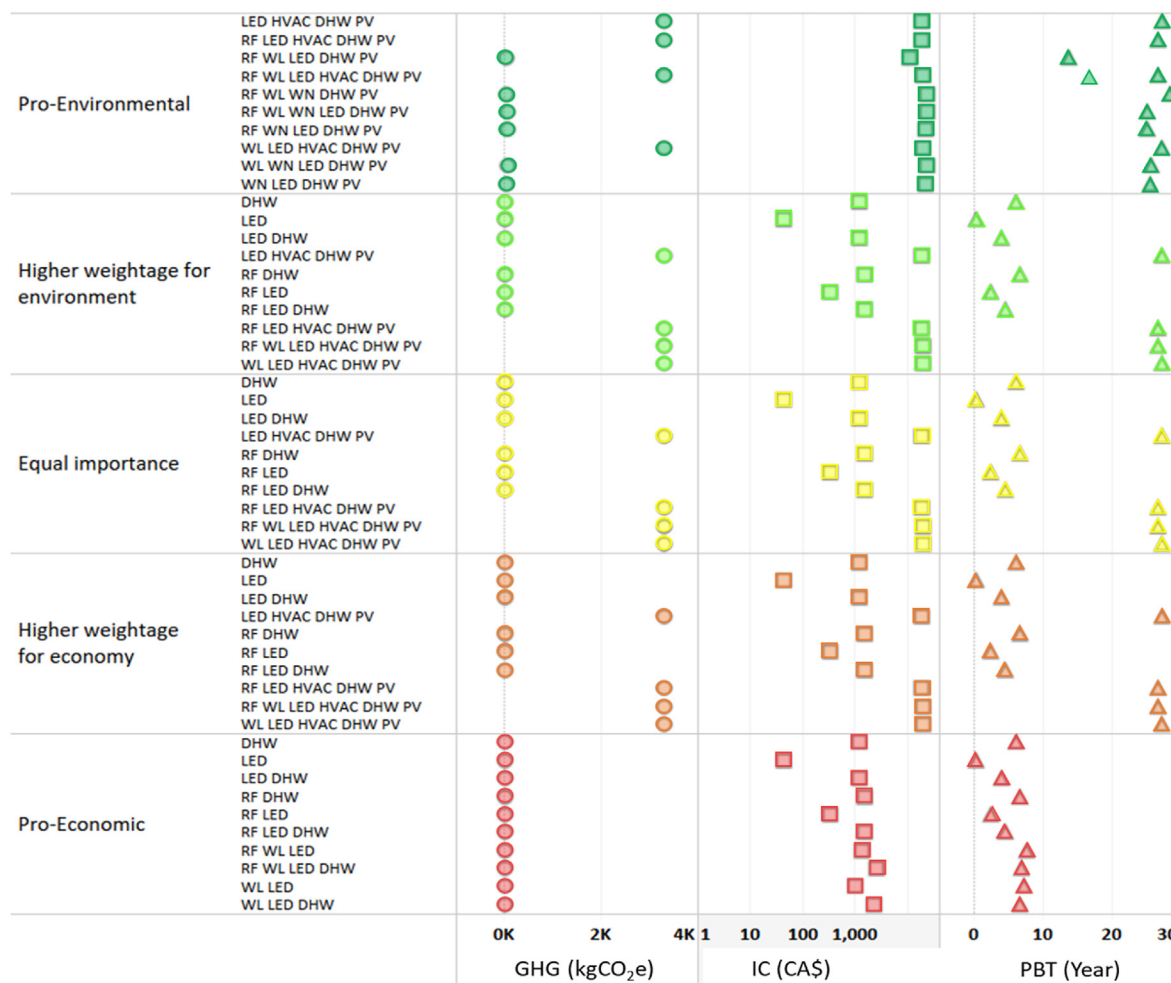


Fig. 11. Comparison between different scenarios- Occupancy Profile 2.

(4.1%) and (7) Other households. Therefore, caution is recommended when applying the results of this study to houses with different occupancy profiles. The type of occupancy profile will affect the amount of energy savings associated with EPU as well as the priority of stakeholders related to investment in energy upgrades. For example, Poortinga et al. (2003) showed that single and senior occupants have a low willingness to invest in energy savings. Similarly, high-income residents consume more energy than low-income earners but are also willing to pay more for energy investments (Guerra-Santin, 2011; Poortinga et al., 2003).

4.3.3. Financial incentives

Financial incentives in form rebates, subsidies, grants are offered to promote the residential building energy upgrades and form a major part of energy policies (Olubunmi et al., 2016; UNEP-SBCI, 2009). These incentives reduce financial risks for investors and help in meeting carbon mitigation goals. A number of financial incentives are also present in British Columbia and other regions of Canada through government and private organizations (NRCAN, 2020). The largest financial incentives are present in the form of rebates offered by local utility providers. Currently, these rebate incentives are available for various household appliances, water heater, heating equipment and insulation (FortisBC, 2020). These incentives were not considered in the life cycle cost analysis, as incentives are subject to change over time as new energy policies and building energy codes are implemented. The inclusion of these

and other government incentives (for a specific time period) will reduce the LCC and change the ranking of the EPU options for the two occupancy profiles.

4.3.4. Other factors impacting EPU ranking

In addition to the occupancy profile other factors can also influence the selection of optimal energy upgrades. For instance the carbon footprint of the energy mix in British Columbia is very low compared to the other regions of Canada (Environment and climate change Canada, 2018). Therefore, the GHG emission reduction potential for energy upgrades will be higher for regions with energy generation based on fossil fuels. Another factor effecting ranking of energy upgrades will be the typology of the house. The energy consumption and the expenditure involved in the installation of the energy upgrades will vary with the type (detached, semi-detached and terraced) of residence (Yohanis et al., 2008). In the current study, single-family detached homes of medium size were considered for framework demonstration. Bastos et al. (2014) study indicates the energy demand and carbon emissions per covered area from large houses is less compared to smaller residences. Compared to large single-family detached homes, multi-unit residential buildings have higher operational energy requirement per unit area. Furthermore, the operation and maintenance cost of apartments are high (Myors et al., 2005). The selection of EPU for multi-unit residential buildings may also be impacted by a commonly observed split-incentive problem due to uneven cost

and benefits distribution between the building owners and renters (Maruejols and Young, 2011). Considering the impact of these factors it is suggested the influence of these factors is not ignored for selection and ranking of EPU's.

4.3.5. Future directions

The existing research can be extended in several directions. Uncertainties involved in the interest rates and future energy prices are an important area of research. Costs of low-emission and renewable systems will be expected to decrease as new equipment and technologies are developed. Hence, the occupants will have more choices of EPU's for making energy-efficient homes and rankings for occupancy profiles will change. Climate change is another important factor that will affect the selection of EPU's in the near future. A recent report by Canada's Changing Climate Report indicates Canada's temperature is rising at rates twice compared to the other regions of the world (Bush and Lemmen, 2019); hence, the cooling load demands of buildings will increase over time. Therefore, future studies should consider the impact of climate change on the EPU's selection for residential buildings.

Another area of research that needs to be addressed urgently is the impact of COVID-19 pandemic on occupant behavior and the relevant EPU's for increased occupancy periods at home. Energy use in residential buildings has increased as people spend the majority of their time at home as an intervention measure (Hinson, 2020). As a result of this pandemic, homes have been transformed into mixed-use spaces where home-schooling, office work, recreational activities, and social interaction has become a norm. Similarly, the percentage of remote or home workers had been steadily increasing in Canada and other countries of the world even in pre-pandemic conditions. Since these trends are predicted to increase over time their influence on energy use and energy upgrades needs to be considered in decision making.

As the next phase of this study, data collected through the load monitoring method will be further analyzed to extract the occupancy patterns for various daily and weekly activities (e.g. sleeping, cooking, dishwashing, laundry, away from home); considering seasonal variations and estimate their impact on energy use and GHG emissions in different types of houses (e.g. semi-detached home, town-house) and/or building characteristics (e.g. envelope, heating and cooling systems). The same occupancy patterns can be used to predict the future study will also use the two profiles to test the effectiveness and efficiency of the existing incentives for achieving energy reduction and GHG emission reduction targets.

5. Conclusions

Residential buildings are responsible for a significant portion of carbon emissions that need to be addressed in order to meet carbon mitigation targets. Studies have shown that energy performance upgrades (EPU's) can help in this regard. However, the impacts of EPU's on a residential building, energy, carbon and cost-effectiveness are significantly influenced by occupant behavior. Limited studies have explored the influence of occupant behavior for the selection of EPU's. The purpose of this research is to provide a framework that is able to assess the effect of occupancy profile on the selection of the most suitable EPU's. Towards this end, a two-step decision support framework is developed that provides direction for comprehensive data collection, development of calibrated energy models, assessment of operational energy, cost and carbon emissions due to EPU's and finally enables prioritization through the use of TOPSIS method.

The application of the proposed framework is demonstrated through comparison between the EPU's needed for two most common energy occupancy profiles in Canada: a family of two

working adults and dependent teenagers and a stay at home retired couple. The study utilizes energy data collected from intrusive load monitoring method to generate calibrated energy models. Calibrated models were tested impacts of EPU's on GHG emissions and payback period. The results showed that for same energy upgrades a family of four is capable of reducing GHG emissions at a higher rate compared to a retired couple. Prioritization for family of four showed that for a pro-environment preference the best option was a combination of "RF WL HVAC DHW PV", while for pro-economic the best option was efficient lighting upgrades. For the retired couple, the best option for pro-environment preference was a combination of "RF WL LED HVAC DHW PV" while for pro-economic choice the efficient lighting upgrades were the best option same as for the family of four. The worst performing upgrade for Occupancy Profile 1 was "RF LED" for pro-environmental behavior while "RF LED HVAC PV" for pro-economic behavior. In the same vein, for Occupancy Profile 2 "LED" was worse performing for a pro-environmental behavior while "RF WL LED APP PV" for pro-economic choice. Hence, it can be concluded that choices of EPU's are limited and similar for different occupancy profiles when pro-economic is the sole criterion for energy upgrade selection while these choices change both in number and rank when decision makers move towards a pro-environmental criterion.

Despite the flexibility of the framework to cater to different occupancy profiles and preferences of investors, the impact of available financial incentives and change of energy prices was not considered. Similarly, the life cycle environmental impacts of energy upgrades are not part of the framework. As buildings become more energy-efficient and construction of net-zero and passive houses become more common, life cycle environmental impacts will become a critical decision making factor. It is recommended that future research especially that focusing on high energy performance houses should consider these factors for prioritization of energy upgrades. The framework is applicable to all kinds of occupancy profiles and can be updated with location and occupancy data. The new understandings from this study can be used for community-level residential building planning. This unique framework can assist developers, planners, potential owners, and practitioners in developing single-family detached houses for retired communities, typical urban communities in Canada and other developed countries.

CRedit authorship contribution statement

Anber Rana: Conceptualization, Methodology, Visualization, Writing - review & editing. **Piyaruwan Perera:** Writing - review & editing. **Rajeev Ruparathna:** Writing - review & editing. **Hirushie Karunathilake:** Writing - review & editing. **Kasun Hewage:** Writing - review & editing, Supervision. **M. Shahria Alam:** Writing - review & editing, Supervision. **Rehan Sadiq:** Writing - review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

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