

An agent-based framework for prioritizing building retrofits

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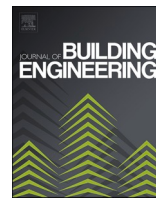
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An agent-based framework for prioritizing building retrofits

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ABSTRACT

As the urgency to address climate change grows, municipalities face the challenge of lowering carbon emissions from buildings, which account for a large portion of total emissions. However, many cities lack the tools and data required to develop effective policies. This study proposes a practical framework for solving this by creating a user-friendly dashboard tailored to the needs of decision-makers in municipalities. The framework analyses current energy consumption, carbon emissions and building characteristics by leveraging existing datasets such as energy assessment databases and the property tax databases. Decision-makers can visualize the potential impact of various retrofit alternatives using scenario analysis and policy simulation, anticipate future construction rates and analyze the embodied carbon impact. The framework provides insights into the current carbon status and targets and enables municipalities to effectively identify and prioritize climate solutions. This paper applies the framework to single-family houses in the City of Victoria, British Columbia, Canada, however its flexibility enables adaption to other contexts around the world. This study adds to the expanding discussion about municipal climate action by proposing a practical, comprehensive approach to inform policy decisions and expedite progress towards carbon reduction targets.

1. Introduction

1.1. Background

Cities and municipalities around the world are struggling with the urgency of mitigating climate change, motivated by the recognition of their important involvement in carbon emissions and the opportunity to adopt meaningful policy changes [1]. The Paris Agreement, with its aim to keep global warming well below 2 °C, emphasizes the crucial need for significant carbon reduction efforts [2]. The Paris Agreement's objectives necessitate a 50 % reduction in carbon emissions by 2030, and cities and municipalities are playing a leading role in combatting climate change.

Buildings appear as a focus area for municipal action in this setting, given their significant contribution to energy consumption and greenhouse gas (GHG) emissions. Local governments play a critical role in advancing sustainable development and climate resilience [3]. Numerous studies emphasize the significance of targeted interventions at the city level in achieving real carbon reductions. However, one persistent difficulty encountered by municipalities is a lack of comprehensive tools and locally relevant data to effectively drive policy decisions.

As of 2018, the building and construction industry was responsible for approximately 39 % of carbon dioxide emissions worldwide [4]. In the City of Victoria, British Columbia, buildings account for 51 % of the greenhouse gas emissions stemming from end-use activities [5]. This emphasizes the critical need to address emissions from buildings in order to achieve climate objectives. Building retrofits, energy efficiency improvements, and the use of renewable energy have all been cited as major techniques for lowering emissions and improving urban sustainability.

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1.2. Literature review

In recent years, the importance of reducing carbon emissions and enhancing energy efficiency in the built environment has prompted a diverse array of research initiatives. Scholars have increasingly integrated data-driven methodologies to better understand the complex interplay between building characteristics, occupant behavior, and retrofit interventions.

Several initiatives have been developed with the aim of assisting municipalities and cities in achieving their climate and energy goals. Among notable initiatives is RETROfitter, which is a decision-support tool developed as part of the TOOLS4CITIES suite at Concordia University [6]. It offers a user-friendly, gamified dashboard for evaluating cost-effective retrofit options. However, its primary focus is on optimizing retrofit measures at the building level without the broader policy simulation component tailored for municipal decision-making.

Another one is the Colouring Cities Research Programme managed by the Alan Turing Institute [7]. It is a network of open-source platforms designed to collect, verify, and visualize comprehensive data on national building stocks. Although Colouring Cities dashboards provide powerful visualizations and data interoperability across cities, they are primarily geared toward open data sharing and research. They do not include decision-making models to simulate retrofit behaviors. NRGYHUB [8] is a Swedish initiative focused on centralizing building energy data and supporting energy management at the municipal level. It is an open data portal for urban energy use and was the first platform in Europe to provide real data on urban energy use. However, it does not include tools to assess the impact of retrofit policies.

An essential facet of this study is the application of data-driven techniques, which recent research has shown to be vital for deriving actionable insights in the building sector. In particular, integrating locally specific data into predictive models has been recognized as a critical driver for informed policy-making, enabling tailored interventions that significantly enhance energy efficiency outcomes [9]. Deb and Schlueter [10] conducted a comprehensive review of building retrofit methodologies, emphasizing the critical role these play in achieving the emission-reduction targets outlined in the Paris Agreement. They contrasted data-driven approaches, which utilize measured building data, with analytical methods, detailing the strengths, weaknesses, and implementation challenges of each. Notably, they identified a hybrid approach combining in-situ measurements with modeling as a promising strategy for developing robust retrofit methodologies. This hybrid approach leverages the accuracy of real-time data and the predictive power of modeling, potentially overcoming limitations inherent in singular methodologies. However, the practical implementation of such hybrid models may face challenges related to data integration and the need for interdisciplinary expertise.

Wei et al. [11] provided a thorough review of data-driven approaches in building energy analysis, focusing on prediction and classification methods. They highlighted applications such as load forecasting, energy pattern profiling, and the formulation of retrofit strategies. Their work underscores the versatility of data-driven methods in enhancing energy analysis at both individual building and urban scales. By refining key tasks within these approaches, they aim to bolster urban sustainability strategies. While data-driven models offer significant potential, their effectiveness is contingent upon the quality and granularity of the input data, as well as the adaptability of the models to diverse building types and usage patterns.

Sun et al. [12] conducted a comprehensive review of building energy prediction methods, emphasizing the growing popularity of data-driven approaches. They addressed gaps in previous literature by providing an in-depth analysis of the entire data-driven process, including feature engineering, model selection, and output expectations. Additionally, they discussed input updating strategies for multi-step predictions and proposed directions for future research. Their work offers a valuable roadmap for researchers and practitioners aiming to implement data-driven energy prediction models. However, the dynamic nature of building operations and external factors necessitates continuous model updating and validation to maintain prediction accuracy over time.

Decision-making in the context of building retrofits and energy efficiency has been extensively studied, with research highlighting the complex interplay between economic incentives, regulatory frameworks, and behavioral factors. Gamtessa [13] developed a theoretical framework to explain residential energy-efficiency retrofit behavior in Canada, considering individual, social, and contextual factors. This comprehensive approach highlights the multifaceted nature of decision-making in energy retrofits, suggesting that policies should not only provide financial incentives but also address social influences and contextual barriers to effectively promote energy-efficient practices.

Lee and Hong [14] employed a hybrid agent-based modeling approach to analyze rooftop solar photovoltaic adoption, integrating geographic information systems and data mining techniques. Their methodology offers a nuanced understanding of how spatial factors and data-driven insights can influence the adoption of renewable energy technologies, underscoring the importance of localized strategies in promoting sustainable energy solutions. Lu et al. [15] introduced a behavior-based decision-making model for energy performance contracting in building retrofits, incorporating perceived benefits, risks, and social influence. This model emphasizes the psychological and social dimensions of decision-making, suggesting that successful energy performance contracts must account for these factors to align stakeholders' perceptions with energy efficiency goals.

Myers and Souza [16] evaluated the effectiveness of social comparison nudges, without monetary incentives, in promoting energy-saving behaviors through home energy reports. Their findings indicate that behavioral interventions leveraging social norms can lead to significant energy reductions, highlighting a cost-effective strategy for encouraging energy-efficient behaviors without relying on financial incentives. Nägeli et al. [17] assessed policies aimed at decarbonizing the Swiss residential building stock using an agent-based building stock modeling approach that incorporates technology diffusion, energy prices, and policy instruments. Their work demonstrates the utility of agent-based models in capturing the complex interactions between various factors influencing policy effectiveness, providing valuable insights for designing comprehensive decarbonization strategies.

In another study, Nägeli et al. [18] proposed a bottom-up modeling approach for agent-based building stock modeling, considering long-term dynamics affecting the energy and climate impact of building stocks. This approach allows for a detailed simulation of

building stock evolution over time, facilitating the assessment of long-term impacts of retrofit policies and the development of strategies that are resilient to future changes.

1.3. Contributions of this paper

This paper seeks to address the crucial need for a comprehensive framework and tool that is applicable to municipal contexts, creating a novel decision-making approach to analyzing and prioritizing building carbon reduction programs. This framework is based on a synthesis of current research, emphasizing the multidimensional nature of the situation and the wide range of remedies available to municipalities.

Using datasets such as the NRCan EnerGuide assessment database and the BC Assessment property tax database, our system employs data-driven modeling tools, including agent-based modeling, to examine present building carbon emissions and estimate future scenarios. The dashboard promotes evidence-based decision-making by modeling various retrofit alternatives, calculating embodied carbon footprint, and estimating construction rates, allowing communities to find and prioritize viable climate solutions. While our research focuses primarily on single-family dwellings (SFDs) in the City of Victoria, the framework's adaptability enables for application to a wide range of municipal situations around the world, with appropriate revision of the underlying assumptions.

The framework introduces several key novelties. While many frameworks focus on broad policy recommendations for reducing building emissions, which often overlooks the practical challenges faced by local governments, our study offers a tailored, data-driven approach that specifically empowers municipal governments. The framework relies on the combination of local property tax data (e.g., BC Assessment) with energy assessment data (e.g., NRCan EnerGuide), creating a more comprehensive and detailed analysis of building stock characteristics, energy use, and carbon emissions.

While agent-based modeling has been used in other contexts, the use of agent-based modeling to simulate individual building owner decisions on retrofitting is a significant contribution. This allows for heterogeneity in decision-making, which more accurately reflects real-world retrofitting behaviors. Accounting for this variation in the response of individuals to the external stimuli provided by municipal policy (among many other factors) is essential in capturing the likely outcomes of particular interventions in a probabilistic manner.

Many existing methods require significant technical expertise to operate or focus on static analysis. But our framework provides a dynamic, scenario-based dashboard that allows non-technical policymakers to interact with the model, input custom parameters, and see real-time projections of different policy outcomes. It introduces an ease of use for non-technical stakeholders combined with robust, data-driven scenario analysis. The framework also prioritizes retrofitting strategies based on their actual energy-saving potential, determined through data-driven insights rather than generic recommendations. This approach allows our platform to be more accessible for the community at large and could improve a municipalities ability to make changes in a timelier manner.

In summary, no prior work combines a comprehensive, data-driven approach with a probabilistic agent-based model of individual behavior to derive insights for municipal decision-makers.

2. Methodology

We have developed a comprehensive framework and toolset that will empower municipalities to analyze and prioritize building carbon reduction policies effectively. Fig. 1 shows the framework components developed in this study. Details of these components are given in the next sections.

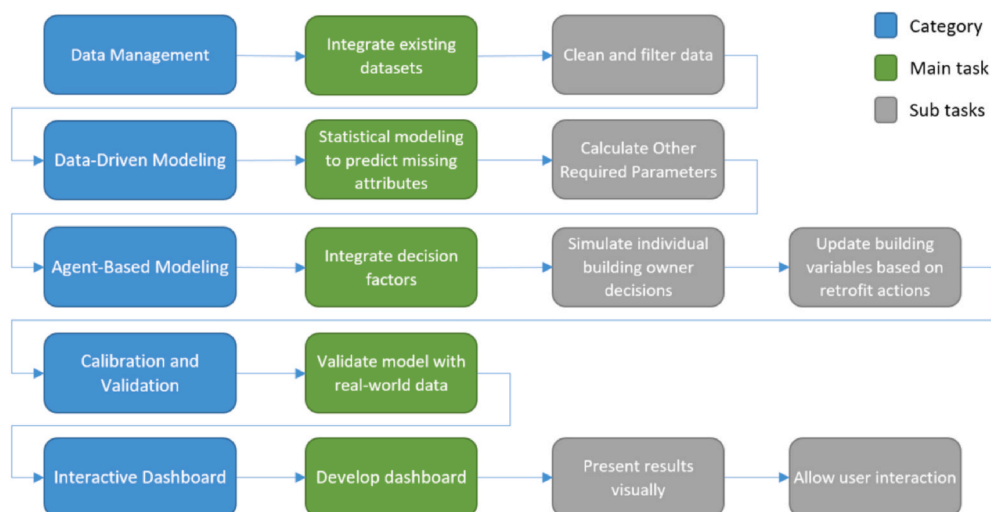


Fig. 1. Flowchart of the whole framework.

2.1. Data management

The framework begins with the integration of existing datasets for the City of Victoria. These databases are.

- **The NRCan EnerGuide assessment database:** Developed by Natural Resources Canada (NRCan), this dataset was generated from EnerGuide home evaluations conducted for residential buildings [19]. The EnerGuide for Houses (EGH) database is a comprehensive repository of information about the energy performance of residential buildings in Canada. It contains data collected from energy evaluations conducted under the EnerGuide Rating System [20].

The EnerGuide Rating System is a Canadian government program that assesses the energy performance of residential buildings. Through this system, certified energy advisors conduct home evaluations, measuring factors like insulation, heating, cooling, and air tightness. These evaluations generate an EnerGuide rating, which helps homeowners understand their home's energy efficiency and potential improvements.

This dataset is a collection of buildings that have gone through the federal retrofit EnerGuide incentive program. With the opt in nature of the program not all buildings within Victoria are accounted for. The database used in this research contains more than 11,000 residential buildings in Capital Regional District (CRD). There are more than 300 attributes available in this database. Table 1 shows a list of most important attributes of this database used in this study.

- **The BC Assessment property database:** Obtained from BC Assessment, the tax authority of British Columbia, the BC Assessment's database contains non-confidential assessment information for all real property in British Columbia [21]. It is a comprehensive resource in British Columbia that provides detailed information on property values and assessments. Managed by BC Assessment, the database includes data on property characteristics such as size, location, and usage, along with assessed values that determine property tax obligations.

Current database used in this research contains more than 9700 residential buildings in the city of Victoria. There are more than 50 attributes available in this database. Table 1 shows a list of most important attributes of this database used in this study.

Both raw databases had some problems, such as numeric data being string, duplicate data, house volume instead of floor area, etc. Which need some processing to be prepared for the analysis. Also, both databases need filtering as they include data for different type of buildings (not only SFDs), and from different regions (not only city of Victoria). Therefore, a rigorous filtering and cleaning processes were done to ensure accuracy and consistency in the later simulations.

2.2. Data-driven modeling

As mentioned in the previous section, the EnerGuide database is not a comprehensive view of the building stock in the City of Victoria, and it only includes buildings that have gone through the federal retrofit EnerGuide incentive program. Approximately 20 % of the SFDs in the City of Victoria have gone through this incentive program and hence have their information in the EnerGuide database.

Therefore, as the BC Assessment database contains the information of all the SFDs in the City of Victoria, this database is considered as the baseline for comprehensive information of all residential buildings. However, as mentioned before, the BC Assessment database only includes data on property characteristics such as size, location and usage, along with assessed values that determine property tax obligations. It lacks the detailed information needed such as energy use, fuel type, retrofits completed etc.

There are precedents for the use of different data-driven techniques such as machine learning to infer missing data [22,23]. Our procedure in this research was to use the EnerGuide database to derive unavailable variables in the BC Assessment dataset, such as energy use, fuel type, etc. The five underlined variables in Table 1 are the ones that have been predicted in this procedure. In this study, Bayesian statistical modeling approaches were used to find out the correlation between different buildings attributes in the EnerGuide

Table 1
List of attributes available in each database used in this study.

EnerGuide	BC Assessment
City	Jurisdiction
Year Built	Year Built
Floor Area	Total Finished Area
Annual energy use	First Floor Area
Main walls insulation RSI value	Second Floor Area
Energy Source	Third Floor Area
Air Source Heat Pump upgrades performed	
Envelope upgrades performed	
Air sealing upgrades performed	
Attic/ceiling upgrades performed	
Windows and doors upgrades performed	
Heating system upgrade performed	
Ventilation upgrades performed	

database, to infer the missing information for all buildings in the BC Assessment dataset. While alternative methods such as machine learning or neural networks might offer competitive predictive accuracy, they typically sacrifice interpretability and explicit uncertainty measures, both of which are key for our application in guiding retrofit policy decisions. Bayesian methods naturally provide uncertainty estimates for model predictions, which is crucial when informing policy decisions where understanding the confidence in forecasted outcomes is essential.

2.2.1. Statistical models

Statistical model makes a prediction based on the model assumptions after using the correlation or relationship between the variables. These models use mathematical equations to make predictions and have a clear understanding of how to interpret the parameters, which can aid in determining how the data relates to one another.

Statistical modeling is used to develop prediction equations for unavailable buildings attributes in the BC Assessment database such as energy use, fuel type, etc. Based on the data available in the EnerGuide database.

The parameters that were modeled in this step are as the following.

- Energy source (Fuel type)
- Energy use
- Wall RSI (Wall thermal resistance)
- Retrofits

The statistical model for retrofits intended to find which building have already undergone each retrofit. Information about several retrofits exist in the EnerGuide database, such as Heat Pump, Envelope, Air sealing, Ventilation, Type 1 Heating System, etc. In this study, only heat pump and thermal envelope are selected for the analysis as they can produce the maximum energy saving in the buildings, based on the data analysis have been done on the EnerGuide database (Fig. 2). In the EnerGuide database, there is information about the energy use of each investigated building before and after upgrades. Through this data we can find what percent each retrofit affects the total energy saving of the considered building. Fig. 2 results are obtained using this method.

This step includes different statistical modeling techniques such as polynomial regression for Energy Use and Wall RSI, and logistic regression for Fuel Type and Retrofits. The procedure for each model is as follows.

- Find the main variables based on assumptions
- Find the correlation between variables
- Develop multiple statistical models
- Compare these models with each other
- Select the best model among the considered models for the prediction

As an example, the steps of statistical model to predict the Wall RSI are as follows.

- 1 The year built and floor area of the buildings are chosen as parameters affecting the wall RSI.

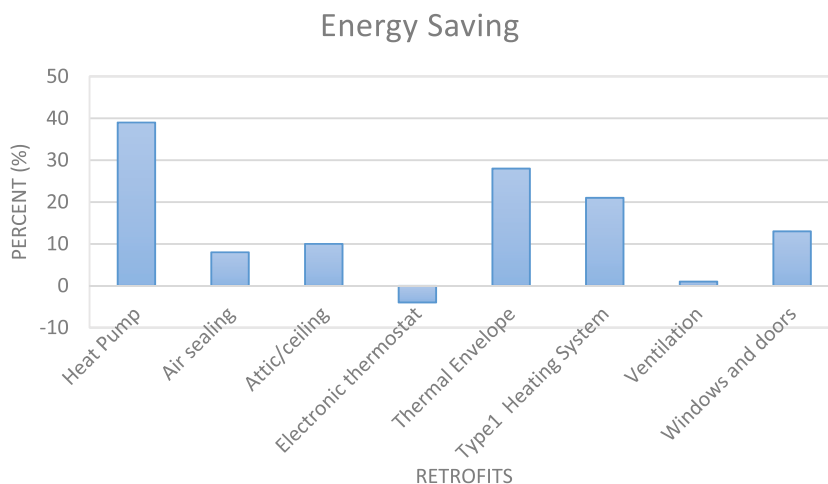


Fig. 2. The energy-saving potential of various retrofit measures.

- 2 A Pearson Correlation is calculated on the available data in the EnerGuide database (Fig. 3). It is seen that Year Built is a more effective parameters than the Floor Area. Therefore, only the Year Built is considered as the independent parameter.
- 3 Here, PyMC (probabilistic programming framework) in Python is used to find the best Bayesian statistical model to fit the data. To do this, eight polynomial equations (from first degree to eight-degree polynomials) are tested to find the best model. To better compare these models, the Expected Log Pointwise Predictive Density (ELPD) of each model is obtained and compared to each other in Fig. 4. ELPD which is a metric used to compare the predictive performance of different Bayesian statistical models based on how well a model fits the data on average across all possible data points it could generate; a higher ELPD value generally signifies a better model fit [24].
- 4 From previous comparison, it is seen that the quadratic polynomial regression produces the best results compare to other considered models. The results of this model are shown in Fig. 5

The same procedure has been done for other variables, i.e. energy use, fuel type and retrofits.

2.2.2. Calculation of other required parameters

After obtaining above parameters for each building in the BC Assessment dataset, we need to calculate other essential parameters for the analysis, including.

- GHG Emissions
- Energy Costs
- Emission Costs

The GHG emissions and energy cost of each fuel type have been obtained from different Resources [25–28] and are summarized in Table 2.

Carbon price (carbon tax rate) is considered as 0.05 \$/kgCO₂e (50 \$/tonne CO₂e) [29] for year 2022. Also, carbon price will increase each year by 0.015 \$/kgCO₂e from year 2023–2030 [30]. The increase in fuels cost due to inflation will be considered as a changing parameter in the dashboard.

To calculate GHG emissions and energy cost of each building in each year, the energy use and fuel type of the building is collected in the previous step using the statistical modeling. It should be noted that the energy use of the building is the Total Energy Consumed, which is the summation of space heating, domestic hot water (DHW), lighting and other electrical appliances. So, even in the buildings with non-electric energy sources (natural gas or oil), some energy is still delivered as electricity. Our database does not say whether the houses have electric or non-electric DHW system, hence we consider all the DHW to be non-electric as this is the dominate case in across the City of Victoria.

Therefore, for buildings with non-electric primary energy sources, the only electric energy use would be due to the lighting and other electrical appliances. The EnerGuide obtaining data methods used by NRCAN assumes constant base loads regardless of building size or how many people are living in it. This default base load for electrical appliances and lighting would be 25622.6 MJ [31].

The following equations is used to obtain the energy cost and GHG emission of the buildings in each year:

$$\text{default_base_load} = 25622.6 \text{ MJ}$$

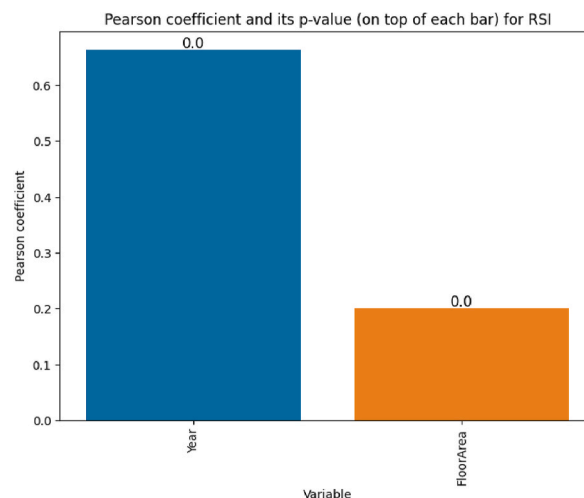


Fig. 3. Pearson correlation for wall RSI based on Year Built and Floor Area.

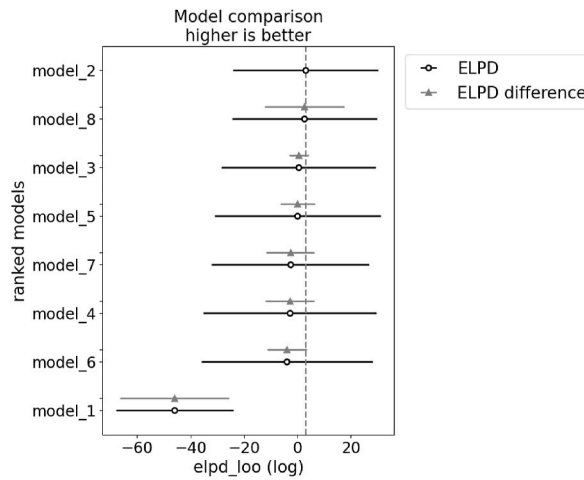


Fig. 4. Statistical models comparison based on ELPD values.

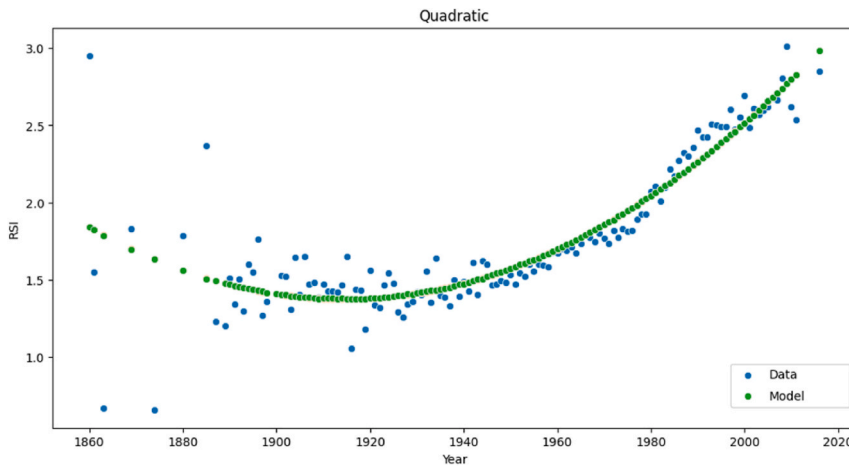


Fig. 5. Quadratic model results vs. data for wall RSI of the buildings.

$$heating_load = energy_use - default_base_load$$

$$fuel_cost_rate = base_fuel_cost_rate \times inflation_rate$$

$$energy_cost = heating_load \times fuel_cost_rate + default_base_load \times electricity_cost_rate$$

$$GHG_emission = heating_load \times fuel_emission_rate + default_base_load \times electricity_emission_rate$$

The base_fuel_cost_rate and fuel_emission_rate for each fuel type are obtained from Table 2, and the inflation rates are input parameters of the simulation.

2.3. Agent-based modeling

An agent-based model has been developed to mimic individual building owner decisions on retrofitting and other energy-related actions. This model integrates key decision-making factors such as financial incentives, energy savings, social influence, and policy triggers. Agent-based modeling is particularly suitable for this context as it allows for capturing the heterogeneity in decision-making across a diverse population of building owners. This is used to model stock development by simulating individual decisions at the building level. The decision model predicts retrofitting behavior based on variables such as energy audit information, costs, and the availability of government subsidies. These variables are informed by datasets such as the NRCan EnerGuide assessment and the BC Assessment property tax database.

There are several papers that studied the effects of decision-making factors on retrofitting behavior of the buildings. Each one tried

Table 2
Fuel emissions and cost rates.

Fuel Type	Emissions rate (kgCO2e/GJ)	Cost rate (\$/GJ)
Electricity	11.14	35
Oil	68.37	48
Natural Gas	49.87	12.784

to identify key drivers and barriers for the adoption of building energy retrofits based on different locations and a variety of effective variables. We analyzed and compared three of these behavioral decision models which are closest to our research [13,32,33].

In this study we used the decision model developed in Ref. [33], where Frondel and Vance introduced a framework incorporating heterogeneity analysis to account for variations in retrofit behavior among households. This study explored the role of information from energy audits in home efficiency improvements using German household data. The model used by Frondel and Vance closely links to our study based on the availability of the examined effective variables in our databases and the results.

The following flowcharts (Fig. 6(a) and (b)) show in detail parts of the Agent-Based Residential Retrofit Model used in this study.

The following part explains how this model predicts future results of the buildings based on different analysis and decision makings.

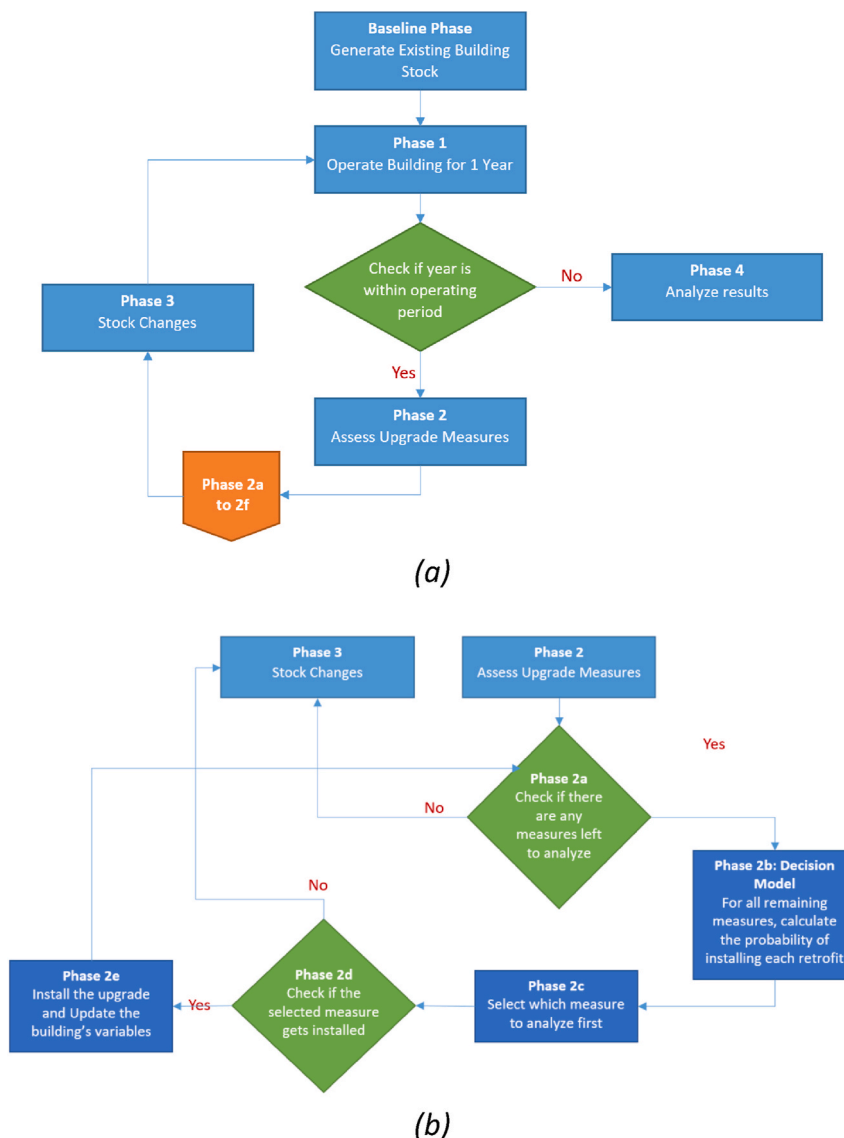


Fig. 6. Flowchart of the agent-based residential Retrofit model.

- **Baseline phase:** At the first of the simulation, the current information of all SFD buildings in the databases are stored for each building individually as an Agent.
- **Phase 1:** Then, the buildings are simulated for the one year to calculate key building variables including energy use, fuel type, GHG emissions, energy cost, etc. Using the methods and formulations explained in the previous section.
- Next, the algorithm will check if the year is within the operating period, which is the time period used in the model to predict the future behavior of the building (here from 2022 to 2030). If yes it assesses the upgrade measures.
- **Phase 2:** This step includes the key calculations that determine what building upgrades will be performed. It includes several steps (shown in Fig. 6(b)) which are related to the decision model processing, as outlined below.
 - o **Phase 2a:** First, the algorithm checks if there are remaining upgrades to be analyzed. If none are available, then it moves on. Otherwise, it goes to the decision model.
 - o **Phase 2b:** The retrofit decision model takes in a number of inputs to calculate the probability that a homeowner will undergo each retrofit independently. Hence, the algorithm calculates the probability of installing each retrofit. This is done, based on the decision model developed in Ref. [33], explained before.
 - o **Phase 2c:** Then, the algorithm randomly chooses which upgrade to analyze first, relative to the respective probability of installation from the previous step.
 - o **Phase 2d:** Next, the algorithm will determine whether or not that upgrade gets installed, based on a binomial distribution of the installation probability. If the upgrade is not installed, then the algorithm ends for the year.
 - o **Phase 2e:** However, if the upgrade is installed then it loops over for the remaining set of upgrades available. Once an upgrade is installed, it updates the building's variables such as energy consumption, cost, GHG emissions, money spent into upgrades, etc.
- **Phase 3:** After these calculations, the process moved to the phase 3, stock changes, which includes adding to the building stock database to keep track of new buildings and removing from the building stock database to account for the demolished buildings.
- These calculations are implemented for each future year based on the affecting input parameters, which can be used to see the effects of different policies.
- **Phase 4:** Finally, after analyzing the obtained results, they used to generate appropriate graphs to show in the dashboard.

2.4. Model calibration

The models go through a thorough calibration process to ensure that they match high-level measured values for the City of Victoria. The first step here is to find reliable reference data from reputable sources, such as.

- **The Capital Regional District Report:** The CRD publishes annual reports detailing various metrics pertinent to the region, including energy consumption, infrastructure developments, and environmental initiatives. These reports provide comprehensive data that are essential for understanding regional energy profiles and setting benchmarks for our models [34].
- **The Victoria Oil Household Survey:** Conducted by City Green Solutions in partnership with the City of Victoria, this survey aims to update records on oil tank usage and assess home heating trends within the city [35].
- **Natural Resources Canada:** As a federal agency, NRCAN provides extensive data and resources on energy usage, efficiency standards, and conservation practices across Canada. Data from NRCAN serve as a national benchmark, allowing us to contextualize Victoria's energy consumption within broader trends [36].

Calibration ensures that the models appropriately represent real-world situations and behaviors. It will entail requesting feedback from stakeholders and experts in municipal climate action to assure the dashboard tool's efficacy and dependability.

Calibration has been performed for the following variables to ensure the model aligns with the real data found in reliable reference sources.

- **Energy Source:** Based on the number of buildings with each specific fuel type (Electricity, Oil, Natural gas) as the energy source from the reference data.
- **Energy Use:** Based on the summation of the energy use in the city of Victoria for each fuel type (Electricity, Oil, Natural gas).
- **Retrofit upgrades:** Based on the number of buildings which have already done each considered retrofits (Heat pump, Thermal envelope).

2.5. Interactive dashboard

The final stage is presenting all obtained results in an easy-to-use dashboard to provide municipalities and cities with a practical yet comprehensive framework for analyzing and comparing the carbon impact of policies enacted by municipal governments.

The interactive dashboard was built using Python, leveraging its powerful libraries for both data analysis and web development. Python's flexibility allows numerical models, such as the data-driven and agent-based models used in this framework, to be rapidly prototyped and tested. Specifically, we utilized libraries like Dash and Plotly to create a web-based interface that visualizes the results in real-time. Python's rich ecosystem for scientific computing, including NumPy and pandas, enables efficient handling of large datasets and complex calculations. Once the models are validated, Python's integration with web technologies facilitates seamless deployment of the tool, allowing municipalities to easily access, run simulations, and explore various policy scenarios through an intuitive, user-friendly web platform. This combination of powerful numerical modeling and flexible web deployment is key to the

tool's practicality.

A user-friendly dashboard interface displays the results of the data-driven and agent-based models, focusing on engaging visuals and simple interactions to make it suitable for non-expert stakeholders. It contains features for comparing different policy scenarios, assessing current status and targets, and evaluating retrofit solutions. The interactive nature of the dashboard allowed stakeholders to adjust input parameters such as fuel inflation rates, upgrade costs, and incentives, and immediately observe the impact on the simulation results. This approach aligns with the principles of mediated modeling [37,38], as it helps create a shared understanding among stakeholders by providing visual and easily interpretable outputs. The ability to interact with the data and simulations encouraged stakeholders to experiment with different assumptions and strategies, making the exploration process more inclusive and grounded in their specific policy context. Some of the results of this dashboard have been shown in the following section.

3. Results and discussion

In this section, the results of the framework are demonstrated to highlight the benefits of this approach. These results are presented in three sections to show different aspects of the dashboard, including current status of the city, future prediction, and policy scenario analysis.

3.1. Current status

At the first, the results regarding the current state of the SFD building stock in the City of Victoria are shown, mainly based on existing data sources. Fig. 7 shows the floor area vs. year build of all the SFD buildings. The solid line represents the average floor area in each year, and the green area shows the variation between 10th and 90th percentiles of the floor area vs. the year build. Although there is not a sharp change in the trend of the floor area of the SFD buildings in different years, the buildings tend to have larger floor area in recent years (after 1990).

Fig. 8 reveals the pre-retrofit (before installing the upgrade) energy use intensity (total energy use per the floor area of the building) vs. year build of all the SFD buildings. Again, the solid line shows the average, and the green area indicates the variation between 10th and 90th percentiles. It is seen that while the average energy use of the buildings approximately doesn't change in the early years (before 1940), it has a constant linear decrease after 1940, which indicates gradual improving in energy efficiency of SFD buildings.

Fig. 9 shows the cumulative annual energy use of all SFD buildings in each year by energy source. The three major energy sources of the buildings are oil, natural gas and electricity. The amount of propane and mixed wood used as energy source is very low and can be ignored. It can be seen that oil was the source of most majority of the energy use of the whole buildings until 1975. However, after 1975, the use of oil has been gradually decreased and the use of electricity increased. Also, the energy delivered as electricity and natural gas were approximately the same until 1970, whereas after that energy delivered as electricity increased compared to natural gas.

Fig. 10 illustrates the cumulative annual operational GHG emissions based on the year range and floor area. Buildings of 160 square meters are the most common, and this aligns with the most GHG emissions. It is clear that the most GHG emissions come from SFD buildings built between 1940 and 1980.

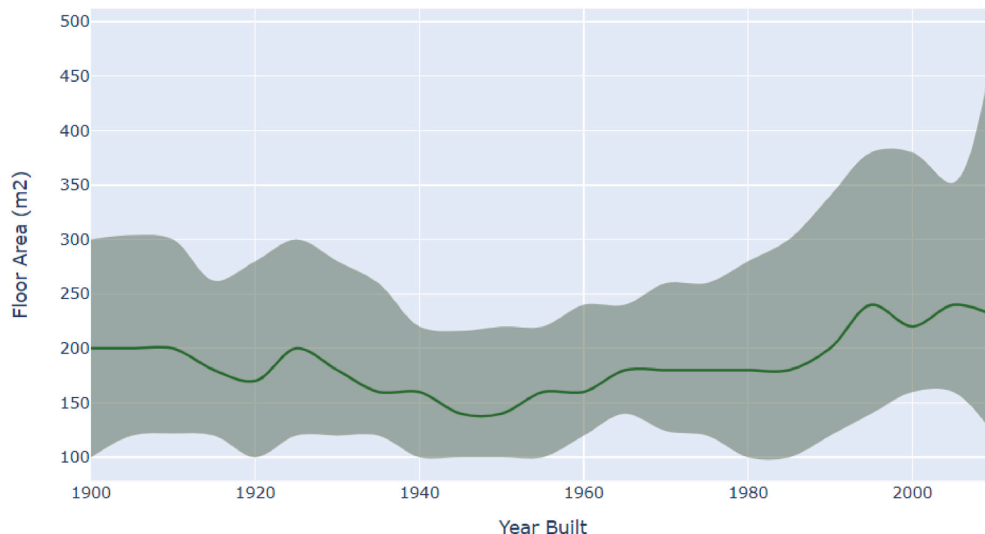


Fig. 7. Floor Area vs. Year Built for all SFD buildings in City of Victoria.

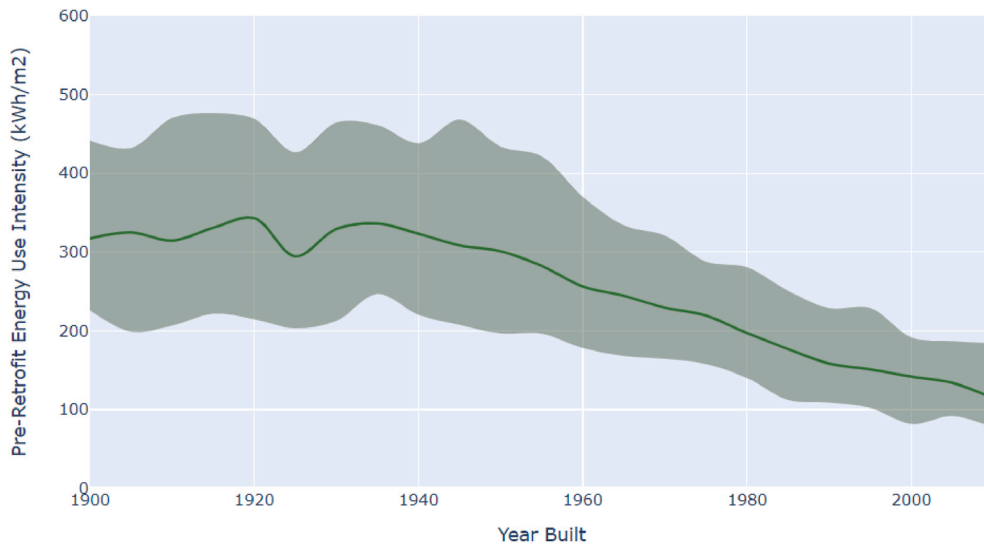


Fig. 8. Average Energy Use vs. Year Built for Single-Family Dwellings.

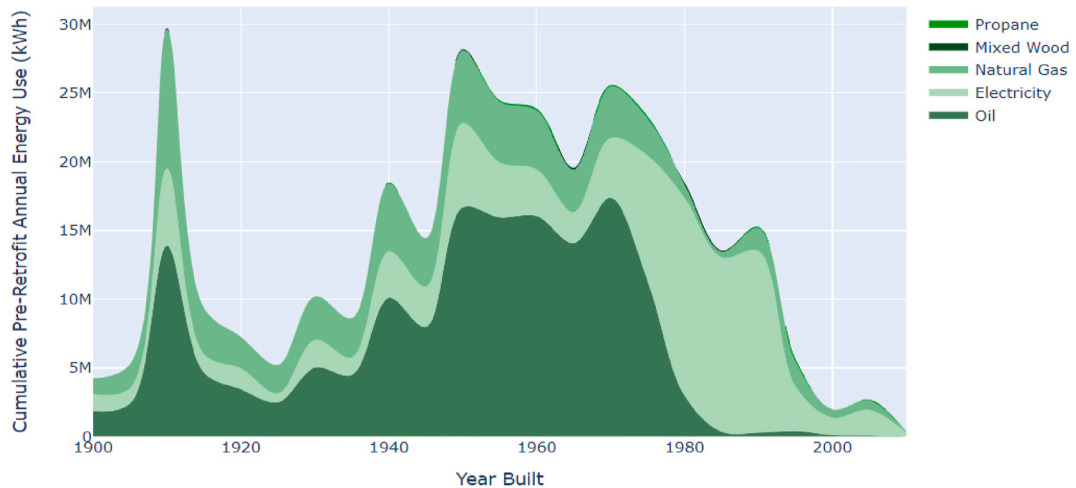


Fig. 9. Cumulative annual energy use by energy source for SFD buildings.

3.2. Future prediction

In the continuation, the results of the simulation are presented. These are the final results obtained after the agent-based model is executed and indicate the future view of the city after applying different targets and options. The examined period of the simulation is from 2022 to 2030, which 2022 represents the current state of the buildings. These results depend on the input parameters. Table 3 shows a sample case of considered input parameters including Fuel inflation rates, Upgrade costs, Upgrade incentives, and Cost inflation rates.

Fig. 11 shows some of the results obtained after running the simulation based on the previous input parameters of the model. It should be noticed that these results are the outcome of applying the current framework and decision model used in this study in order to predict the retrofit upgrades of each building, new constructed buildings and demolished buildings in each year, which is explained in detail in previous sections.

Fig. 11(a) shows the total annual energy use and GHG emissions of all SFD buildings in the city of Victoria in each year. By considering the given costs, incentives and inflation rates as inputs, the total energy use decreases from 320 to 260 GWh, while GHG emissions reduced from 33k to 20k tonne CO₂e, from 2022 to 2030.

Fig. 11(b) shows the total energy use of all SFD buildings by fuel type in each year from 2022 to 2030 after applying input parameters. Current inputs lead to the increase of using electricity and reduction use of oil and natural gas in the city. Oil use reduces substantially which is a goal for City of Victoria policy makers. The variations of energy use are better seen by plotting EUI (energy use

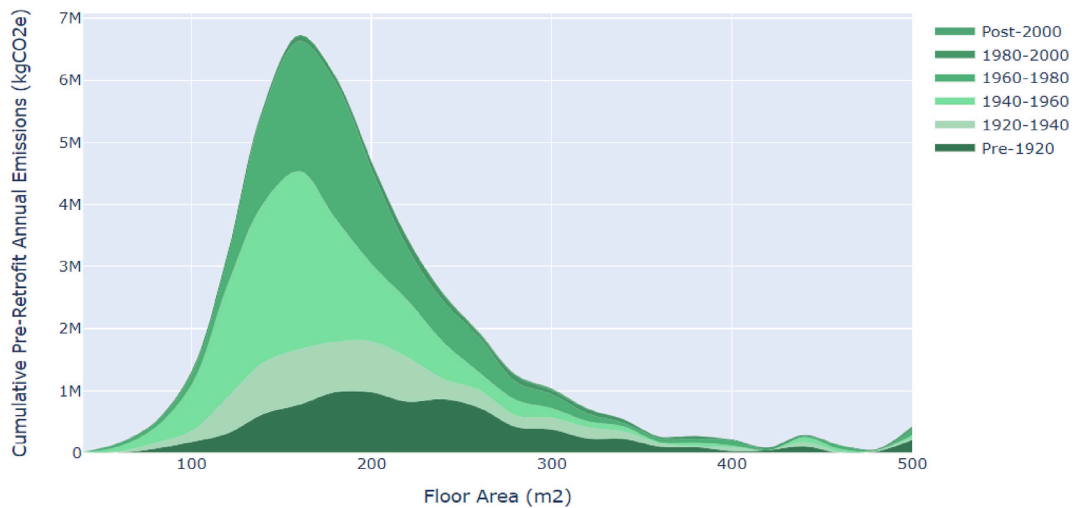


Fig. 10. Cumulative annual operational GHG emissions vs. year range and floor area.

Table 3

Input parameters for fuel inflation rates, upgrade costs, and incentives.

Category/Item	Value	Unit/Notes
Fuel Inflation Rates		
Electricity	3 %	Annual inflation
Oil	3 %	Annual inflation
Gas	3 %	Annual inflation
Measures Cost		
Heat pump base cost	\$4250	One-time
Heat pump linear rate	\$50	per square meter
Envelope base cost	\$3	per square feet
Measures Incentive		
Heat pump incentive	\$2000	One-time
Envelope incentive	\$3000	One-time
Measures Inflation/Incentive		
Heat pump cost inflation	3 %	Annual rate
Envelope cost inflation	3 %	Annual rate
Heat pump incentive increase	2 %	Annual rate
Envelope incentive increase	2 %	Annual rate

intensity) of different energy sources on each studied future year in Fig. 11(c). This figure shows that despite the decrease in total energy from oil, the intensity of this energy source is so much higher than electricity and natural gas. Again, it can be seen that energy from oil is reduced much more than either the increased use of electricity or decreased use of natural gas.

Fig. 11(d) reveals the total operational emissions of all buildings in each future year based on each energy source. Despite the low number of oil buildings in the city (less than five percent according to databases of the city), they have the largest amount of GHG emissions at the current studied year, 2022. Which is the main reason the policy makers in the city intend to convert all of oil energy source buildings, with retrofit upgrade to other type of energy sources. This figure shows that current considered inputs can reduce the amount of GHG emissions of oil buildings from 14k to 2k tonne CO₂e. The GHG emission of natural gas buildings are also reduced. Although, the GHG emission of the electricity buildings is slightly increased due to the increase of the conversion from other energy sources to electricity, however, the total GHG emissions of all buildings is dramatically decreased at the end of studied year, 2030.

Total operating cost (including both energy and emission costs) are shown in Fig. 11(e) for each studied year. It predicts the reduction of total cost in each upcoming year, which is due to implementing more efficient retrofits, reduction of energy and GHG. The total cost reduction is about 18 % for the considered input parameters, which a promising outcome that motivate more people to do retrofitting.

Fig. 11(f) shows the percentage of all retrofit upgrades installed in each studied year. As it is expected, the maximum number of upgrades occurs in early years, which decreases in each following year. These changes can be seen better in Fig. 11(g), which shows the percentage of each retrofit separately in each year from 2022 to 2030. It is seen from Fig. 11(g) that although both envelope and heat pump installation increases in each future year, however the rate of increase of envelope retrofit is higher than heat pump. It should be highlighted that the input parameters such as upgrade costs and incentives have a direct effect on these results, and with changing these parameters, policy makers can reach to different results based on their desired policies.

Fig. 11(h) presents the total upgrade cost and incentive of all buildings in the city in each year which is very useful data. It can be

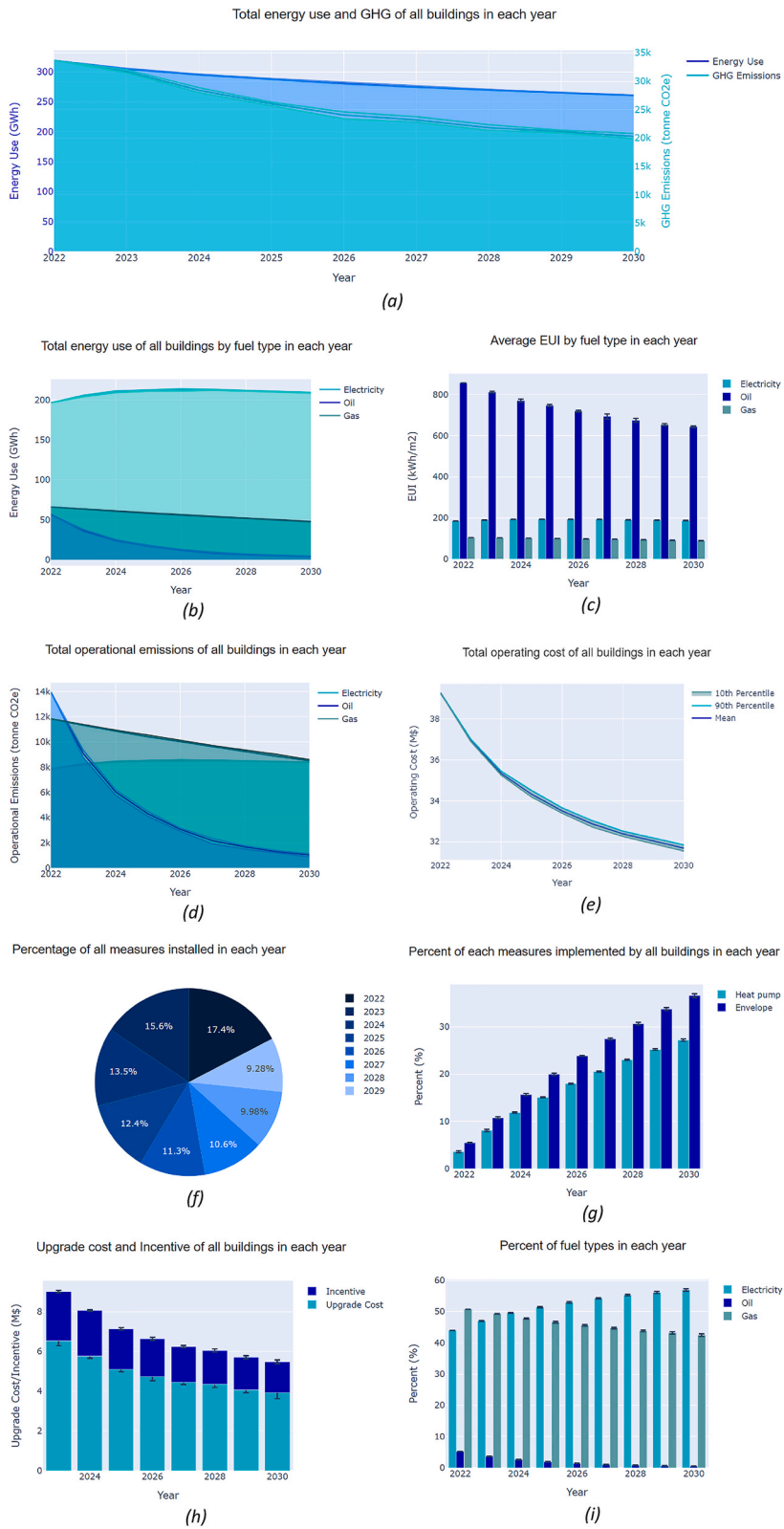


Fig. 11. Simulation results of energy use, emissions, retrofits, and cost changes from 2022 to 2030.

used to predict the amount of needed costs and incentives to reach the desired goals. Finally, the change of fuel type (energy source) percent of all SFD buildings are shown in Fig. 11 (i) for each studied future year. The percentage of buildings with electricity fuel type increases each year, while oil and natural gas fuel types reduce, which were expected based on the previous results. The percent of oil buildings reduces to 0.5 percent until 2030 based on the current considered input parameters, which is a desirable outcome.

3.3. Policy scenario analysis

One of the main goals in this study is to visualize real-time projections of different policy outcomes. Here, some results are presented for visualizing and comparing policy scenarios. Among the input parameters, cost of retrofit installation and upgrade incentives are two of main influential parameters.

Figs. 12 and 13 show the results of different heat pump base costs and incentives on the prediction of various simulation results, respectively. Here, for both heat pump base cost and heat pump incentive, three scenarios are considered to compare the results with amount of 2000\$, 5000\$, and 10,000\$. As can be seen from Fig. 12, decreasing heat pump base cost slightly decrease the total energy use and operating costs of all buildings in each year. Also, the lower heat pump cost obviously led to increasing the number of heat pump upgrades in each year, but on the other hand it slightly decreases the number of envelope retrofits undertaken.

Incentives are one of the key factors that policymakers can leverage to influence the motivation to upgrade installations. They also serve as an important parameter for determining how much should be allocated to achieve policy goals. Fig. 13 illustrates the impact of increasing heat pump incentives on retrofitting, demonstrating how the incentive amount affects adoption rates. The results indicate that increasing incentives has a more significant positive effect on reducing total energy consumption and operating costs for all buildings in the city compared to lowering heat pump costs (as shown in Fig. 12). Additionally, the adoption of heat pumps is higher in this scenario than in the case of reducing heat pump costs. Since lowering heat pump costs may not be feasible or practical, the findings

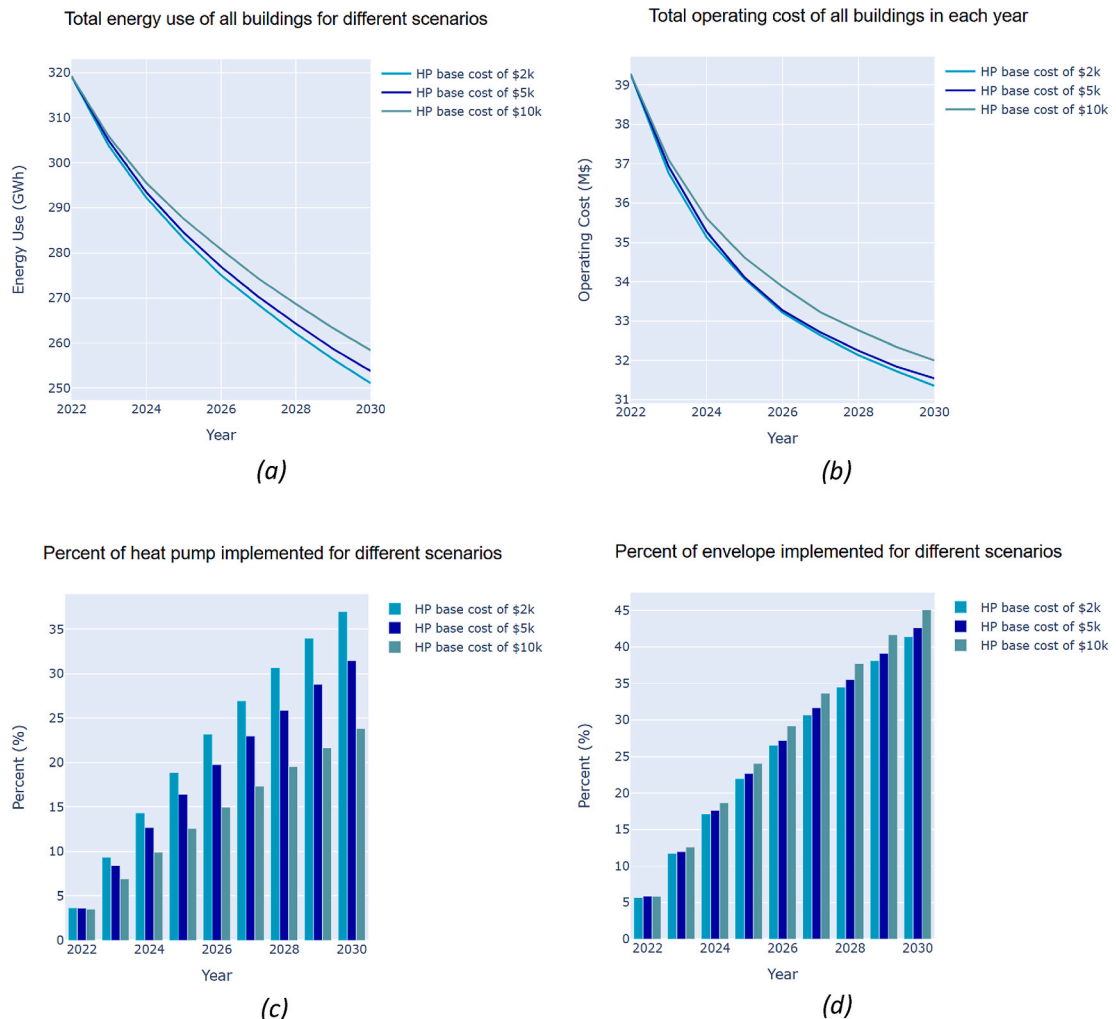


Fig. 12. Impact of varying heat pump installation costs on retrofit adoption and energy use.

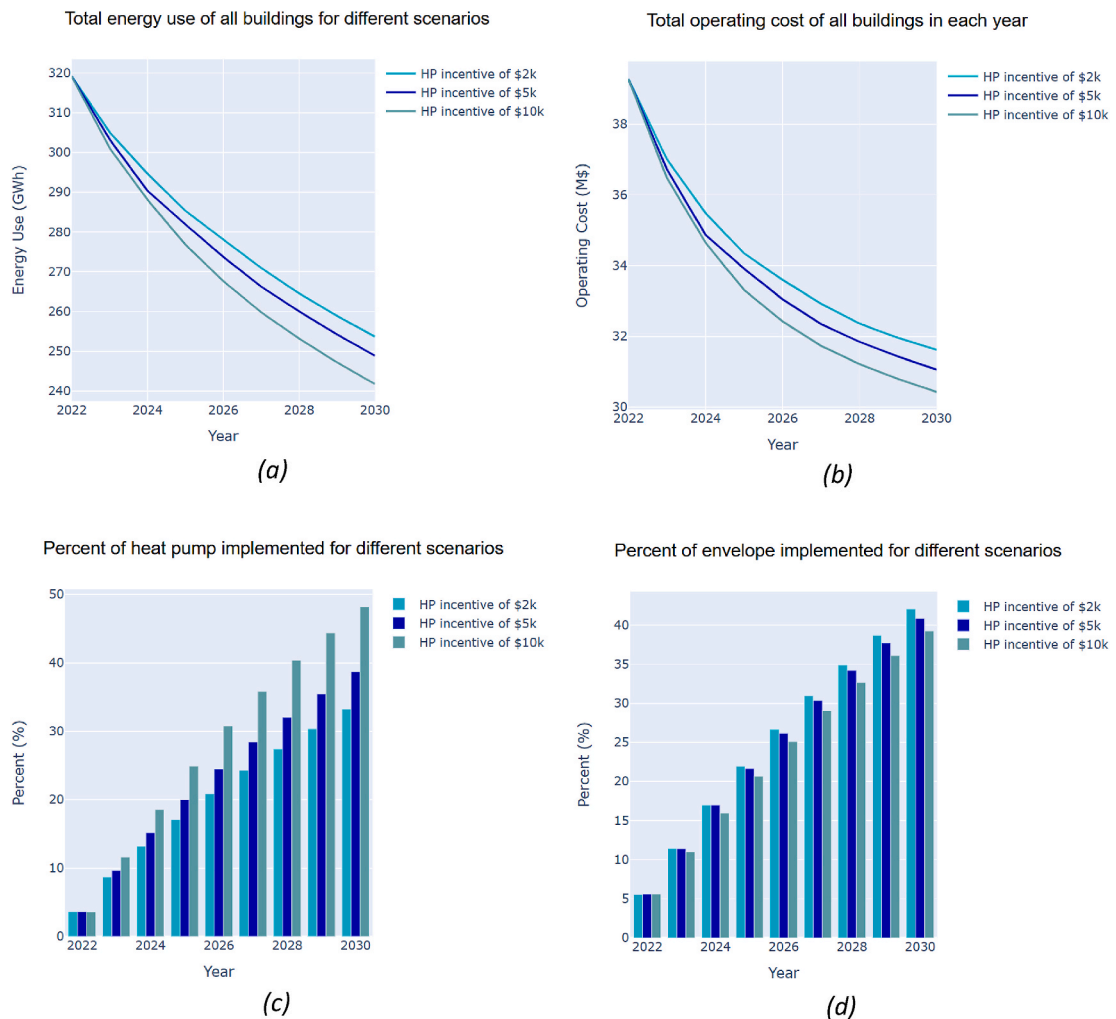


Fig. 13. Impact of different heat pump incentive levels on retrofit adoption and energy use.

suggest that increasing incentives is a more effective policy for achieving energy reduction goals in the city.

4. Conclusions

This study presents a framework and associated software tool to assist municipalities in efficiently reviewing and prioritizing building carbon reduction programs. It intends to give decision-makers actionable insights to solve the critical challenge of lowering carbon emissions from buildings by utilizing data-driven and agent-based modeling methodologies, as well as the development of a user-friendly dashboard application.

The research aims to bridge the gap between climate objectives and effective policy actions at the municipal level by meticulously collecting data, modeling, and developing tools. The methodology aims to assure the correctness, reliability, and usability of the generated framework and toolset by synthesizing existing datasets, using advanced modeling techniques, and incorporating stakeholder feedback.

This paper focuses on the energy consumption, GHG emissions related to single-family dwellings in the City of Victoria. However, the framework has been developed in such a way that it can be replicated by municipalities and cities worldwide when paired with appropriate datasets. There are inherent limitations in the use of EnerGuide scores, as with all sources of data regarding the building stock; on the aggregate level, however, this data provides an adequate view of the building stock for retrofit policy planning purposes.

Despite its inherent limitations and uncertainties, this study is an important step towards empowering governments to expedite progress toward carbon reduction goals and improve urban sustainability. By delivering evidence-based insights and concrete suggestions to decision-makers, the framework and tool have the potential to spark significant action in the global battle against climate change.

While the current study focuses on two primary retrofit measures, we acknowledge the need to expand the scope to include all other

measures initially presented. Future research will incorporate these additional retrofit strategies, enabling a more comprehensive evaluation of policy interventions. Furthermore, we plan to enhance the model's flexibility, allowing municipalities to test and compare various retrofit policies dynamically. This will involve integrating improved parameter customization, conducting sensitivity analyses, and validating model predictions against real-world retrofit adoption data.

In conclusion, this study adds to the expanding body of knowledge on municipal climate action and emphasizes the value of data-driven approaches in influencing policy decisions and generating transformative change. Municipalities can utilize the resulting dashboard to identify and prioritize climate solutions that align with their stringent commitments.

CRedit authorship contribution statement

Khosro Lari: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Investigation. **Kevin Cant:** Project administration, Methodology, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Ralph Evins:** Writing – review & editing, Supervision, Project administration, Methodology, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Khosro Lari reports financial support was provided by Natural Sciences and Engineering Research Council of Canada. Ralph Evins reports a relationship with Building Atlas Ltd that includes: consulting or advisory and equity or stocks. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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