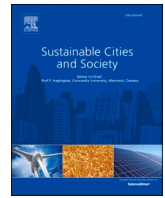




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How residential energy consumption has changed due to COVID-19 pandemic? An agent-based model

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ABSTRACT

Integrating occupant behavior with residential energy use for detailed energy quantification has attracted research attention. However, many of the available models fail to capture unseen behavior, especially in unprecedented situations such as COVID-19 lockdowns. In this study, we adopted a hybrid approach consisting of agent-based simulation, machine learning and energy simulation techniques to simulate the urban energy consumption considering the occupants' behavior. An agent-based model is developed to simulate the in-home and out-of-home activities of individuals. Separate models were developed to recognize physical characteristics of residential dwellings, including heating equipment, source of energy, and thermostat setpoints. The developed modeling framework was implemented as a case study for the Central Okanagan region of British Columbia, where alternative COVID-19 scenarios were tested. The results suggested that during the pandemic, the daily average in-home-activity duration (IHD) increased by approximately 80%, causing the energy consumption to increase by around 29%. After the pandemic, the average daily IHD is expected to be higher by approximately 32% compared with the pre-pandemic situation, which translates to an approximately 12% increase in energy consumption. The results of this study can help us understand the implications of the imposed COVID-19 lockdown with respect to energy usage in residential locations.

1. Introduction

Given the unprecedented COVID-19 lockdown measures, many people are spending more time at home than at any period ever. This behavior is likely to continue to some extent after COVID-19 due to the longer-term impacts of this pandemic such as our inclination towards continuing to work from home. Therefore, urban residential energy demand is likely to increase greatly in the coming years. The increase in residential energy consumption presents several challenges, including urban heat island effect (Halder, Bandyopadhyay & Banik, 2021; Roshan, Sarli & Grab, 2021; Wang, Berardi & Akbari, 2016) climate change (Boyd, Pathak, van Diemen & Skea, 2022; Guyadeen, 2019; Milojevic-Dupont & Creutzig, 2021), and equitable distribution of home energy cost burden (Andor, Frondel & Sommer, 2018), which has significant implications in building sustainable cities and societies. To address these challenges, improved quantification of energy consumption is required to assist in developing effective equitable plans and policies.

The literature shows that residential energy consumption is largely

dependent on occupants' behavior, lifestyle, in- and out-of-home activities, and utilized technologies in dwellings (Jin et al., 2020; Li & Yao, 2020). Several techniques are used to quantify the residential energy consumption. One of the popular techniques is the bottom-up approach, which refers to modeling the energy use of each household and its components collectively (Abbasabadi & Mehdi Ashayeri, 2019; Chingcuanco & Miller, 2012; Todeschi, Boghetti, Kämpf & Mutani, 2021). Bottom-up urban energy models can be categorized into three groups: statistical models, simulation models, and a hybrid of the statistical and simulation techniques (Chingcuanco & Miller, 2012). The statistical models typically use historical billing data and accommodate occupants' behavior based on historical records. One of the limitations of this method is its inability to incorporate new and alternative energy technology scenarios. Moreover, this approach might not be efficient to capture unprecedented changes in the occupants' behavior, such as the significant longer stay-at-home behavior during the COVID-19 pandemic (Abbasabadi & Mehdi Ashayeri, 2019; Chingcuanco & Miller, 2012). On the other hand, the simulation models are capable of testing the effects of alternative energy technologies. However, they

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require intensive data and more sophisticated computation hardware is needed to run the models that lack the behavioral representation of the occupants as behavior is generally assumed. Nevertheless, developing a hybrid urban energy model that encompasses statistical and simulation modeling techniques can capitalize on the advantages of both approaches while mitigating the limitations of each (Abbasabadi & Mehdi Ashayeri, 2019; Chingcuanco & Miller, 2012). For instance, in a hybrid urban energy modeling system, statistical models can be used to represent the in-home (IH) and out-of-home (OH) activity behavior of the household members, which can be used as input for an energy simulation model.

Recognizing human IH activities is essential for residential energy simulation, which includes but is not limited to telework and online learning (Bubb & Jones, 2020; Tanpipat, Lim & Deng, 2021), online shopping, and personal maintenance such as IH cardio activities (Bubb & Jones, 2020; Tanpipat et al., 2021). The need to model IH has been highlighted during the COVID-19 pandemic, as individuals stayed at home longer due to travel restrictions and social distancing measures (Fatmi, Thirkell & Hossain, 2021). Individuals started to substitute or complement numerous OH activities, such as travel to work, with IH activities, work from home, and virtual care (Jones et al., 2020). This transformation reshaped the daily OH and IH activities (Fatmi et al., 2021), as well as shifted the burden of energy cost from employers to employees (Mahfuz Alam & Ali, 2021). This change in daily activities increased residential energy usage significantly (Mahfuz Alam & Ali, 2021).

Many of the existing residential models that depend on historical records lack the means to capture unseen changes in the occupants' behaviors. For instance, in the long term, such as after the pandemic, individuals might retain many of their behaviors during the lockdown by continuing to work from home and/or working on flexible hours. This presents the need to adequately capture individuals' activity behavior using the simulation tools, and consequently improve the prediction of the change in residential energy consumption before, during, and after the pandemic. Such an understanding of residential energy consumption can assist in developing effective climate emergent and equitable energy security plans and policies. This condition will assist in better understanding and promoting sustainable and socially resilient cities.

This study adopts a hybrid of agent-based model (ABM), machine learning (ML) technique, and energy simulation tool to model and simulate urban IH activities and associated energy consumptions. ABM is a modeling paradigm that enables us to describe the state, properties, and behavior of any agent at a certain amount of time. Moreover, the ABM facilitates capturing the complex interactions among agents' decisions in an environment, which is of particular interest when addressing the complexity of urban decision-making processes. The proposed ABM assumes that the agents are individuals and households, and simulates their daily activity behavior and state, including IH and OH activities, heating equipment of dwelling, energy source, thermostat set points, and operated electric appliances in various situations (e.g., while the occupants are sleeping or outside their dwelling). To represent occupant behavior within this ABM framework, we adopt ML and heuristic techniques. Data for the modeling and simulation is from the Central Okanagan region of British Columbia, Canada. The agent-based model is integrated with the energy simulation platform EnergyPlus to simulate the energy consumption of the agents. The EnergyPlus is developed by the US Department of Energy and has been used extensively in the literature (Mokhtari & Jahangir, 2021; Monfet, Charneux, Zmeureanu & Lemire, 2009; Tian, Love & Tian, 2009; US Department of Energy, 2021; Zirnelt & Richman, 2015). Many studies tested the accuracy of the EnergyPlus versus actual records from energy bills in different parts of the world (Ancuss D Signelković, Mujan & Dakić, 2016; Queiroz, Westphal & Ruttkay Pereira, 2020; Tabares-Velasco, Christensen & Bianchi, 2012). The spatial resolution of this integrated ABM and energy model is the individual parcel level, enabling simulation at the micro-spatial resolution of the buildings. The specific

objectives of this study are to:

- Utilize ML models to predict the state and properties of individual agents such as in-home activity duration (IHD), thermostat setpoints, and heating equipment within an agent-based modeling framework; and
- Integrate the agent-based model with an energy simulation tool to simulate the agent's behavior and corresponding residential energy consumption so that alternative scenario testing, such as before, during, and after the pandemic, can be conducted.

The presented work aims to propose multidisciplinary research in areas related to urban and transportation systems and their interaction with residential energy consumption. It also covers aspects related to behavior modeling and analysis using ML and artificial intelligence applications. The significance of this study is in providing a policy-sensitive model that can simulate the in-home activity of individuals at their dwelling and the resulting energy consumption in a different context. The importance of such a model revolves around better understanding of how the COVID-19 affected individuals' in-home activity and accordingly, their residential energy consumption to help effectively promote environmentally friendly solutions for large-scale studies, such as those on cities. The contributions of this study are the following: 1) integrating ML techniques with agent-based simulation to predict the regional residential energy consumption, 2) integrating individual occupants' behavior while simulating urban energy, and 3) developing and testing novel scenarios to predict how residential energy consumption has evolved from pre- to during- to post-pandemic periods.

2. Literature review

The outbreak of the COVID-19 pandemic created unprecedented action plans that prompted many people to change their behavior. The literature is rich with studies that analyze the implications of the pandemic from several perspectives. For example, Ghahramani and Pilla (2021) explored the underlying association between the number of confirmed COVID-19 cases and socioeconomic characteristics of various geographical regions in Dublin, Ireland. The researchers adopted an ML approach to identify demographic characteristics and spatial patterns. According to the analysis, seven clusters were detected based on the census data and the spatial distribution of the people were explored using unsupervised neural network method. A study by Aral and Bakir (2022) investigated the spatiotemporal pattern of the COVID-19 spread in Turkey. The results revealed that the population density and elderly dependency ratio were crucial in explaining the new COVID-19 confirmed cases. Moreover, the authors highlighted the influence of geolocation context represented by neighboring provinces in affecting the COVID-19 cases Khavarian-Garmsir, Sharifi and Moradpour (2021). assessed the risk of compact urban development to contain the pandemic. The authors investigated the association between urban density and the spread of the virus through a case study of Tehran, Iran. The authors found that urban density alone could not be considered a risk factor for the spread of COVID-19 because density did not explain the geographic pattern of the spread (in terms of confirmed cases and deaths) across the municipal districts of Tehran. However, a study by Liu, Liu and Guan (2021) showed a different conclusion. The authors assessed the impact of the built environment on the COVID-19 rate in King County, US, by developing multiple linear regression and geographically weighted regression models. Their findings illustrated that the built environment was positively associated with COVID-19 cases, i.e., increased open space would reduce the number of such cases. Another study by Cuervo-Vilches, Navas-Martín, March and Oteiza (2021) conducted an online survey to explore the behavioral response of households in Spain given their new needs during the lockdown. The authors conducted an online survey of 256 households consisting of people who either telework or study from home. Their

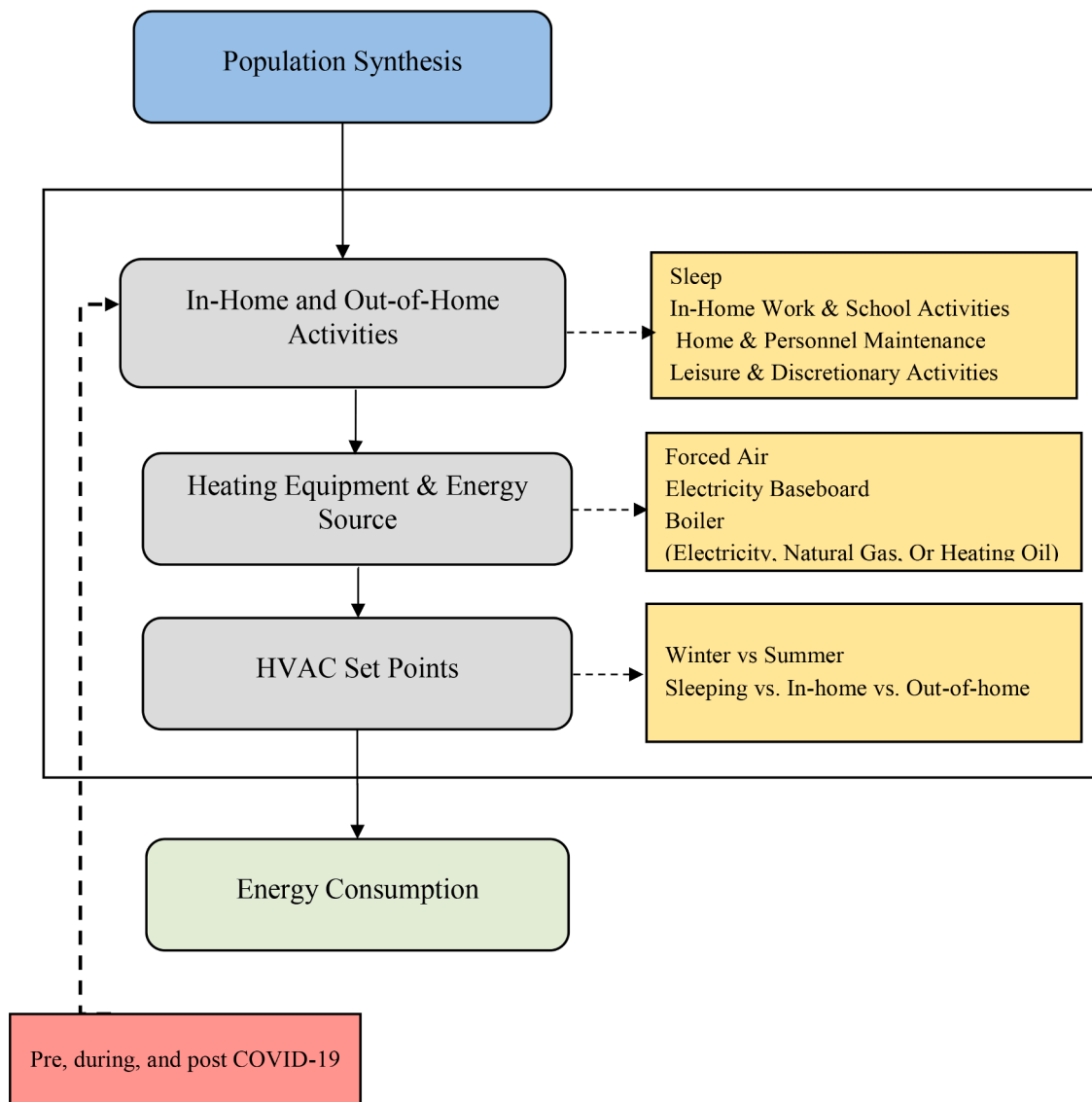


Fig. 1. Modeling Framework of Agent-based Energy Microsimulation Model.

results showed that the acceptability of telework spaces were insufficient for a third of the households, and had no significant relationship with most of the socioeconomic variables nor with home characteristics.

Many studies have attempted to simulate energy-related consumption in the context of COVID-19. For instance, [Balest and Stawinoga \(2022\)](#) conducted a survey covering approximately 3500 people in Italy to study the changes in their daily habits, including their in-home energy use. The survey collected data on socio-demographic and household characteristics. Their findings were interpreted according to the social practice approach applied in the past, such as cooking. Another study by [Abulibdeh \(2021\)](#) investigated how water and electricity consumption changed in Doha, Qatar across six sectors before and during the COVID-19 lockdown. Spatial maps for each sector were prepared for the following periods: pre-lockdown, lockdown, easing lockdown, and post-lockdown. The author utilized Moran's I, Anselin Local Moran's I, and Getis-Ord G_i^* tools to identify the hot and cold spots of water and electricity consumption for each sector in the study area. The findings show spatial and temporal heterogeneities in water and electricity consumption across the different sectors, where the commercial and industrial sectors had the highest consumption. Interestingly, the author found that during the lockdown period, the water and electricity consumption respectively increased by 6% and 30% in 2020 compared with

the rate in 2019. Another study by [Nguyen \(2021\)](#) utilized three datasets to compare the impact of the COVID-19 lockdown on spatiotemporal electricity across different classes in the United States. In the spring of 2020, the author found that the weekday residential consumption resembles weekend profiles in previous years. At the same time, the total commercial consumption declined, but the daily consumption profile was unchanged. In fact, the author claimed that the impact of COVID-19 was dampened because changes in residential loads and non-residential loads had a similar magnitude but moved in opposite directions. A study by [D Zhang et al. \(2021\)](#) summarized major statistics of energy supply and demand before and during the pandemic across different sectors in Macao. The authors indicated that overall, the energy consumption exhibited a downward trend. The imposed policy during the COVID-19 spread not only declined in energy but also reduced carbon emissions and consequently improved the environment. However, the authors highlighted that this type of energy-saving scheme that restricts human activities and hinders economic development has major drawbacks. Another study by [Ding, Ivanko, Cao, Brattebø and Nord \(2021\)](#) compared the electricity use patterns of four buildings before and during the COVID-19 lockdown. The buildings considered in their study included kindergartens, schools, apartments, and townhouses in Norway. The authors simulated three scenarios to test various operation

strategies, namely, operating under normal settings, operating of educational buildings under nighttime and weekend settings, and operating of residential buildings under work-at-home conditions. Their results indicated that the electricity demand could be reduced by one-third by following the second scenario. For the third scenario, the electricity consumption could increase by approximately 27% and 1.3% for townhouses. Other works in the literature studied the effect of COVID-19 on energy at different scales and from various perspectives, such as energy consumption of single buildings (Gerald, Bavaresco, Triana, Melo & Lamberts, 2021), effect of COVID-19 on energy returns (Saif-Alyousfi & Saha, 2021), and the role of occupant distribution on energy consumption during the pandemic (Mokhtari & Jahangir, 2021).

As the results show, most of the available studies conducted an aggregate analysis on how the energy consumption changed during the pandemic. This type of analysis may not fully capture the behavior of individuals with respect to energy consumption. For instance, the heterogeneous nature of individuals' behavior could prevent those aggregate modeling/analyses from providing a comprehensive analysis of the effect of COVID-19 on energy consumption and demand. Moreover, those studies lack the potential to simulate future policy scenarios with regard to the pandemic. A thorough review by Benita (2021) on human mobility behavior during the pandemic concluded that studies related to the understanding of changes in travel behavior, such as telecommuting, are insufficient. Accordingly, the link between such travel behavior and energy consumption is also lacking. Additionally, many of the previous models utilized simple econometric models to estimate the activity durations. The emergence of ML techniques might provide a compelling alternative given the superiority of their performance in predicting many other research problems. This study aims to address these research gaps by proposing a disaggregate ABM model utilizing ML techniques to simulate residential energy consumptions considering the change of individuals' behavior before, during, and after the COVID-19 pandemic.

3. Methods

3.1. Modeling framework

Fig. 1 shows the modeling framework, which includes the following components: population synthesis, modeling the in-home and out-of-home activity prediction, predicting the heating equipment and source of energy, estimating the thermostat setpoint, and finally simulating the residential energy consumption before, during, and after the pandemic.

The population synthesis component generates the input information of the agents at the individual level such as age and gender, and household level such as dwelling type and income. The synthetic population is generated using a Bayesian network modeling technique, which is described by Rahman and Fatmi (2022). Thereafter, we developed ML models to predict the IH and OH duration of each agent in an urban area. The IH and OH activity component simulates the type and duration of daily activities. This study focuses on the in-home activities, which are categorized into the following groups: sleep, leisure, and discretionary activities (LDA) such as relaxing, socializing, watching television and participating in religious/spiritual activities, home and personnel maintenance (HPM) such as general household activity, house cleaning, and personal care, and mandatory activities such as remote work and online learning. The heating equipment and source of energy components predicts the type of heating equipment such as forced air furnace, electricity baseboard, and boiler; and the type of main source of energy is electricity, natural gas, and heating oil. ML techniques are adopted to assign the heating equipment and main source of energy to each dwelling. The thermostat set point component assigns temperature based on time of the year (i.e., winter or summer) and activity type (i.e., IH awake or sleeping and OH). The current version of the model uses probability density function to vary thermostat setpoints over a day based on the season and activity type. Finally, the output from the previous stages, including the decisions of the agents, and the built

environment or urban region, such as parcel characteristics, were used as the input for the energy simulation tool, that is, EnergyPlus. The current version of the agent-based model is developed using the Matlab environment integrated with EnergyPlus to perform a simultaneous simulation. The output of the energy simulation model is main heating equipment, source of energy, thermostat setpoints at various situations, and building energy (appliances and cooling), all for each building unit in the study area.

3.2. Simulation procedures of agent-based modeling

In this study, the following ML techniques were considered: artificial neural network, regression trees (RT), ensemble and support vector machine (SVM), k-nearest neighbor (KNN), (only for the source of energy modeling), and Gaussian process regression (GPR). Interested readers could refer to these references for more details about each technique (Kubat, 2017; Mathur, 2018; Menšík, Duží, Albert, Patschka & Pajr, 2019). To test the accuracy of the developed ML models, the following performance measures were used:

$$\text{MeanSquareError(MSE)} = \frac{1}{n} \sum_{i=1}^n (\hat{y}_i - y_i)^2 \quad (1)$$

$$\text{RootMeanSquareError(RMSE)} = \sqrt{\text{MSE}} \quad (2)$$

$$\text{MeanAbsoluteError(MAE)} = \frac{1}{n} \sum_{i=1}^n |\hat{y}_i - y_i| \quad (3)$$

$$\text{R-Squared} = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (4)$$

$$\text{Overall Accuracy} = \frac{\text{True Positive} + \text{True Negative}}{\text{All Records}} \quad (5)$$

The ML models will be applied within the agent-based modeling framework to simulate individuals daily IH and OH activities, and their durations, and the main heating equipment (MHE) and source of energy (SoE) of each dwelling. The simulation will be performed for the 24-hour period of a typical weekday for the winter season. The current study only considers single-detached dwelling (SDD). First, we simulated the OH duration using the ANN model. One of the reasons for simulating the OH prior to the IH models is the availability of a large sample size from the OTS regarding OH activities (more than 5000 records). Then, we simulated IH activity participation using the SVM and ensemble models for HPM and MAND activities, respectively. We assumed that every individual agent would perform sleep and LDA activities. Following assigning IH activity type to each individual, their corresponding duration is simulated using GPR models. After determining the durations of both OH and IH activities, we performed a check so that the total duration does not exceed the daily 24-hour time budget. To simulate MHE, each dwelling was assigned with one of the following MHE options by applying the ensemble tree model: force air furnace, electric baseboard, and boiler. In the case of the SoE, the medium KNN model was used to assign one of the following options: electricity, natural gas, and oil.

In the case of simulating cooling/heating system setpoints, PDF was used based on data from the HES-2015. These data provided information on individuals' behavior toward thermostat setpoints at different conditions: setpoints during winter while the individuals are sleeping and awake in-home, and similarly in summer while the individuals are sleeping, OH, and awake IH. The current version of the model used a PDF for this component. Each condition described above was simulated in two steps. First, it is determined whether the thermostat is turned on or off, and second, if it is on, the setpoint is assigned. We developed PDF models for each scenario. This decision was based on a preliminary ML

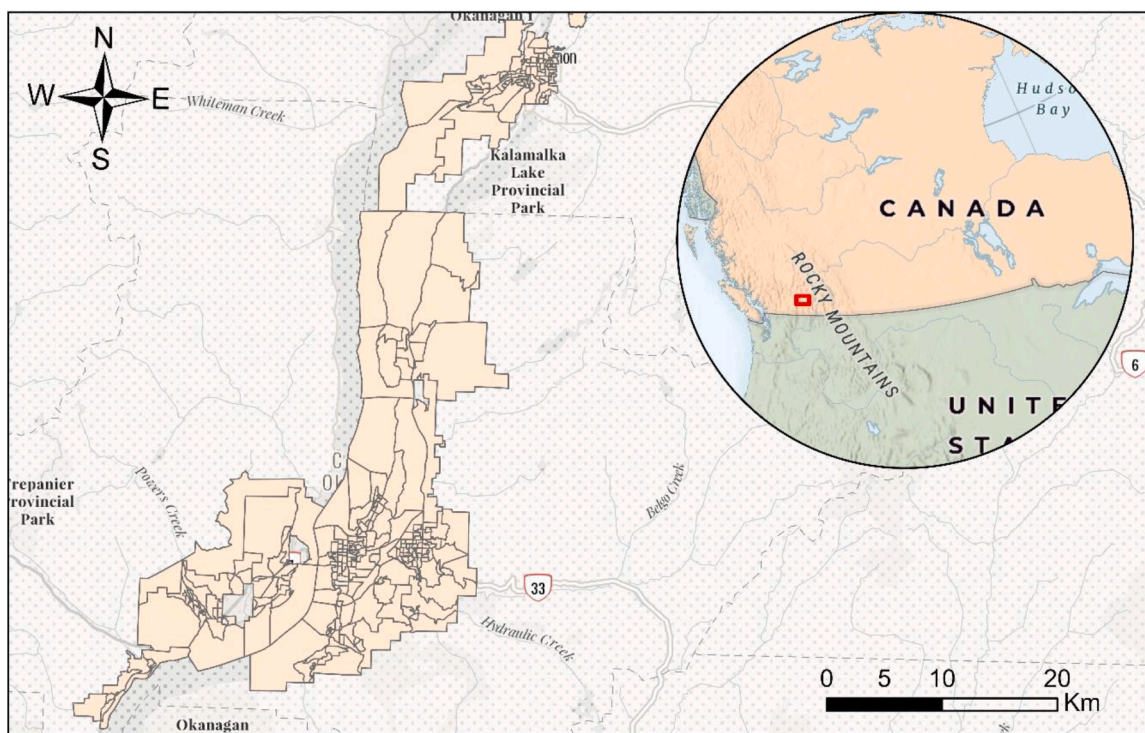


Fig. 2. Study Area.

modeling for the scenarios, which did not reveal robust accuracy. Thus, modeling simpler PDF models were more computationally efficient without risking the compensation of significant accuracy. A binomial distribution was chosen for the thermostat on/off model for each condition, and a normal distribution was adopted to assign the setpoints.

3.3. Study area and data

The agent-based urban energy model is developed and tested for the Central Okanagan region of BC, Canada (Fig. 2). This region includes the cities of Kelowna, West Kelowna, Lake Country, Peachland, and Vernon. Kelowna is the third-largest metropolitan area in BC after Vancouver and Victoria. It has an area of approximately 210 km² with a population of around 190,000 people. Kelowna is classified to have a humid continental climate. In winter seasons, the average temperature ranges between -3 and 0 °C, whereas in summer, the average temperature is about 16 °C.

This study uses data from several sources. First, the database of the COVID-19 Survey for Assessing Travel Impact (COST) for the Central Okanagan region, BC, Canada, was utilized (Hossain, Haque & Fatmi, 2020). The COST survey collected information on OH trips and IH activities before and during the COVID-19 travel restriction. The survey was conducted between March 24 and May 9, 2020. The data are validated against the census information for the Okanagan region, which can be found in Fatmi et al. (2021). A total of around 200 individuals were surveyed. The COST data were utilized for modeling IH activity (i.e., sleeping, mandatory activities, HPM, and LDC) participation and duration. Second, the 2018 Okanagan Travel Survey (OTS) was utilized to model the OH activities. The OTS collected information on daily travel for each household member including, but not limited to, location, arrival and departure time, purpose, accompanying person, and mode from the residents of the Central Okanagan region (Smart Trip Okanagan Travel Survey). More than 5000 records were retrieved, and further details of OTS could be found in Smart Trip (n.d.) and Smart Trip Okanagan Travel Survey, 2018 (n.d.).

Third, we used the database of the Households and Environment

Table 1
Summary of Collected Inputs for Model Development Stage.

| Variables | Categories |
|-------------------------------|---|
| Number of People in Household | 1, 2, 3, 4, or 5+ people |
| Age | 0 to 9, 10 to 14, 15 to 19, 20 to 24, 25 to 29, 30 to 34, 35 to 39, 40 to 44, 45 to 49, 50 to 54, 55 to 64, 65 to 74, and 75+ years |
| Gender | Female and Male |
| Employment Status | Employed, unemployed, or not in the labor force |
| Occupation | Management, administration business and finance; natural and applied sciences; health services; education, law and government services; art, culture and sport; sales services; trades and transport; natural resources & agriculture; manufacturing and utilities; and others (people who are less than 15 years of age) |
| Dwelling Type | Single detached dwelling |
| Household Income | Under \$10,000; \$10,000 to \$19,999; \$20,000 to \$29,999; \$30,000 to \$39,999; \$40,000 to \$49,999; \$50,000 to \$59,999; \$60,000 to \$69,999; \$70,000 to \$79,999; \$80,000 to \$89,999; \$90,000 to \$99,999; \$100,000 to \$124,999; \$125,000 to \$149,999; \$150,000 to \$199,999; and \$200,000 and over |
| Education | No certificate, diploma or degree; high school certificate; trades certificate; certificate of apprenticeship; college certificate; university certificate (below bachelor level); Bachelor's degree; Graduate certificate; and Others (people who are less than 15 years of age) |
| Built-up Year | 1960 or before; 1961 to 1980; 1981 to 1990; 1991 to 2000; 2001 to 2005; 2006 to 2010; and 2011 to 2016 |

Survey (HES) of 2015 by the Canada Census (Statistics Canada, 2019). In brief, the HES offers an expanded information dwelling's main heating equipment and source of energy, thermostat set points at different seasons under several conditions, kitchen and yard waste, hardware waste, and household income. Additional details of HES 2015 could be found in Statistics Canada (2019). The three databases were utilized to prepare the following factors: dwelling type, built-up date range, number of people in the household, gender and age of each person, employment

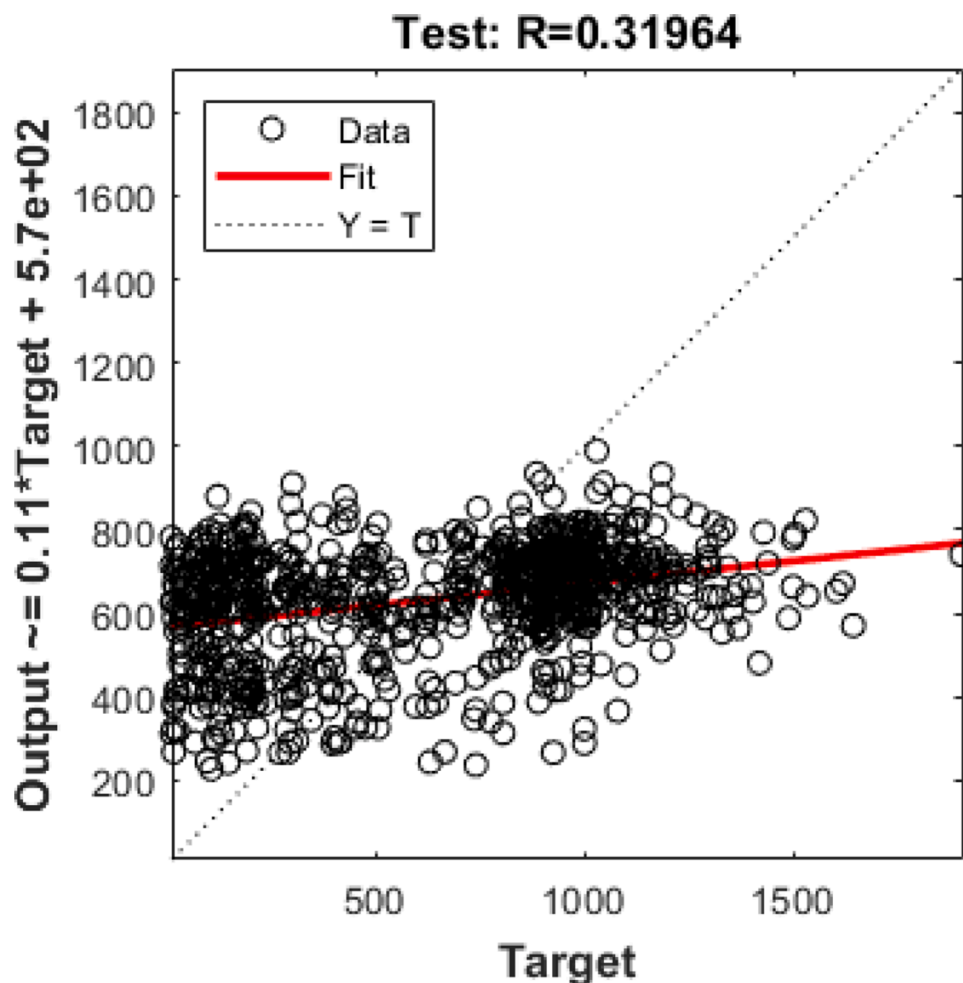


Fig. 3. Predicted versus Measured OH Duration.

and occupation status, number of vehicles in the household, marital status, and household income. These were used to develop the ML models and PDFs (TABLE 1)

The COST, OTS, and HES were readily processed from the source. Therefore, we had to conduct a minor pre-processing by removing missing records to ensure the compatibility of all datasets. Further exploration about the data could be found here (Khalil & Fatmi, 2022).

3.4. Machine learning models

In this section, we explain the developments of ML algorithms we carried out for the following components of the model: IH participation and duration, OH duration, main heating equipment, and source of energy. We briefly describe the methods and highlight their performance. Note that the input data for the simulation engine are generated through a population synthesis procedure described by Rahman and Fatmi (2022). The input variables that were used in all the following models are shown in TABLE 1. The model development was conducted based on a five-fold cross-validation to mitigate any biases in the results. Accordingly, all the presented results and tables related to the ML models' performance are based on actual data support.

In the IH and OH activity component case, this study used a simplified version of the OH component. Specifically, the OH duration is modeled, as it is essential to check with the IH duration and match the daily time budget of 24 h. One of the reasons for estimating OH prior to the IH models is the availability of a large sample size from the OTS.

Several ML algorithms were attempted, but the most accurate algorithm reported in our trials was artificial neural network (ANN) (Ali

Khalil, Hamad & Shanableh, 2019; Khaled Hamad, Ali Khalil & Shanableh, 2017). The ANN is a popular model that has been used in multiple domains in the literature and generally provides superior results over other ML tools. As known, the ANN contains input, hidden, and output layers. The hidden layer contains multiple neurons in each, which could be translated as the complexity between the connection of the input and output layers. Usually, a higher number of neurons are used with a complex model, but an excessive number of neurons could result in overfitting. Thus, we have to highlight that the dataset was divided into subgroups for training, validation, and testing. The primary purpose of this division was to prevent overfitting and obtain objective performance measures that were not biased toward the training dataset (Ali Khalil et al., 2019; K Hamad, Khalil & Shanableh, 2016.; Khaled Hamad et al., 2017). The training dataset was used to develop the model, while the validation dataset was used to determine the termination of the training based on the decay of the model's performance, and the testing dataset was used to provide the performance of the model on an unseen dataset Fig. 3. shows the predicted OHD versus the measured values for the testing dataset. As shown, the coefficient of correlation (R) is equal to 0.32, which indicates moderate accuracy. The MSE of the best model was 151,281.

In the case of the IH activities and duration, four activities are considered: sleep, MAND, LDA, and HPM. First, we estimated the participation model for HPM and MAND activities using a classification ML algorithm. In the case of LDA and sleep, we assumed that each individual will perform these activities every day. Based on the outcome of the participation models, an ML duration model for each IH activity was estimated. The best participation model for HPM was the SVM-Fine

Table 2
Performance of ML Models for MHE.

| Model Type | | MHE | | | |
|------------|-----------------|------------------|--------|--------|--------|
| | | Overall Accuracy | TP (1) | TP (2) | TP (3) |
| ANN | 10-neuron | 79.5% | 88.9% | 80.5% | 9.1% |
| | 25-neuron | 79.6% | 89.0% | 80.3% | 10.9% |
| | 100-neuron | 79.4% | 88.8% | 79.0% | 14.2% |
| RT | Coarse tree | 78.1% | 84.9% | 87.1% | 0% |
| | Medium tree | 80.9% | 89.4% | 82.4% | 16.2% |
| | Fine tree | 80.8% | 89.1% | 81.7% | 19.2% |
| Ensembles | Boosted tree | 80.8% | 88.9% | 83.0% | 15.8% |
| | Bagged tree | 80.6% | 89.3% | 81.3% | 16.5% |
| | Subspace KNN | 69.8% | 87.1% | 53.2% | 2.6% |
| | RUBoosted Trees | 75.6% | 80.0% | 72.5% | 55% |
| SVM | Linear | 68.5% | 90.5% | 42.2% | 0.8% |
| | Quadratic | 76.1% | 87.0% | 75.9% | 0% |
| | Cubic | 67.0% | 71.4% | 72.9% | 15.8% |
| | Fine Gaussian | 79.3% | 88.9% | 80.2% | 8.0% |
| | Medium Gaussian | 79.5% | 88.4% | 83.2% | 4.6% |
| | Coarse Gaussian | 69.0% | 90.5% | 44.5% | 0% |

*TP (1): True Positive for forced air furnace.

**TP (2): True Positive for electric baseboard.

***TP (3): True Positive for boiler.

Gaussian model with an overall accuracy of 97.3%, false positive accuracy of 29.4%, and negative accuracy of 0%. On the other hand, the best participation model for the MAND was the ensemble bagged tree model with an overall accuracy of 93.9%, false positive accuracy of 8%, and negative accuracy of 4.3%. To improve the computational efficiency of IH duration, the activities were normalized to improve as follows: Sleep\LDA (SleepDur), HPM/IHD (HPMD), and MAND/IHD (MANDD). The GPR model achieved the highest accuracy with the following measures:

- SleepDur: RMSE: 0.63, R2: 0.94, and MAE: 0.27
- HPMD: RMSE: 0.03, R2: 0.87, and MAE: 0.01
- MANDD: RMSE: 0.07, R2: 0.74, and MAE: 0.03

Further details on the modeling could be found in the work of [Khalil & Fatmi, 2022](#).

In the case of modeling the MHE and SoE, individual sociodemographic and dwelling characteristics are used. Two separate ML classification models were developed to predict the MHE and SoE, respectively. The current versions of the models were developed for single-detached dwelling (SDD) only. The MHE considered three options: force air furnace, electric baseboard, and boiler. Several ML techniques were attempted, but the ensemble trees model ([Hastie, Tibshirani & Friedman, 2009](#)) had the highest overall accuracy and true positive accuracies for the three types of MHE, as shown in [TABLE 2](#). The confusing matrix of the model ([Fig. 4](#)) suggests that option 1 (i.e., forced air furnace) had an accuracy of 80%, and option 2 (i.e., electric baseboard) had a 72.5% accuracy. However, for option 3 (i.e., boiler), the model was only able to predict it accurately 55% of the time. All these accuracies are based on five-fold cross-validation.

The SoE model, on the other hand, considered three options: electricity, natural gas, and oil. Similar to the MHE, several ML models were attempted, and the best model appeared to be medium KNN, as shown in [TABLE 3](#) [Fig. 5](#). shows the conclusion matrix of the mentioned model where the overall accuracy was 80.5%. In detail, option 1 (electricity) had an accuracy of 28.1%, option 2 (natural gas) was 95.2% accurate, and option 3 (oil) was 62.8% accurate.

Data from the HES-2015 were used to estimate the thermostat set-points. The data provided information about individuals' behavior toward thermostat setpoints during winter while the individuals are sleeping and awake in-home, and in summer while the individuals are sleeping, OH, and awake IH. The current version of the model used a PDF for this component. Each condition described above was modeled in two steps: first, determine whether the thermostat is turned on or off, and second, if it is on, determine what the setpoint is. We decided to develop PDF models for each scenario. This decision was based on a preliminary ML modeling for the scenarios, which did not reveal robust accuracy. Thus, modeling simpler PDF models were more computationally efficient without risking the compensation of significant accuracy. Based on the HES-15 records, the binomial distribution was chosen

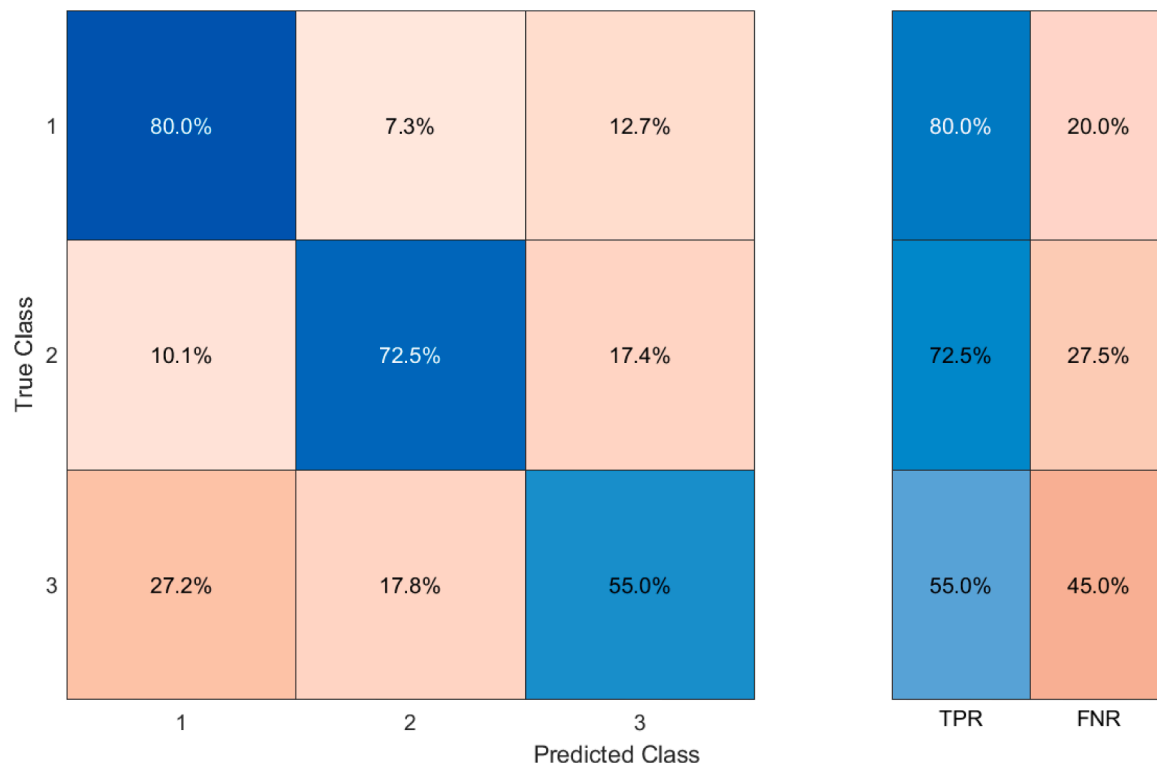


Fig. 4. Confusion Matrix of MHE Ensemble Trees Model.

Table 3
Performance of ML Models for SoE.

| Model Type | | SoE | | | |
|------------|-----------------|------------------|--------|--------|--------|
| | | Overall Accuracy | TP (1) | TP (2) | TP (3) |
| ANN | 10-neuron | 81.3% | 24.2% | 97.1% | 63.5% |
| | 25-neuron | 81.2% | 26.6% | 96.5% | 63.0% |
| | 100-neuron | 80.9% | 26.6% | 96.2% | 62.6% |
| RT | Coarse Tree | 81.5% | 22.1% | 97.7% | 64.1% |
| | Medium Tree | 81.5% | 22.5% | 97.7% | 63.8% |
| | Fine Tree | 81.1% | 25.9% | 96.7% | 61.5% |
| Ensembles | Boosted Tree | 81.4% | 22.9% | 97.5% | 64.1% |
| | Bagged Tree | 81.2% | 24.6% | 97.1% | 62.3% |
| | Subspace KNN | 75.0% | 23.1% | 90.5% | 51.0% |
| SVM | RUBoosted Trees | 79.0% | 47.1% | 88.5% | 64.7% |
| | Linear | 79.2% | 0.0% | 99.6% | 64.1% |
| | Quadratic | 80.4% | 14.4% | 98.0% | 64.1% |
| KNN | Cubic | 73.9% | 14.4% | 88.9% | 65.1% |
| | Fine Gaussian | 81.0% | 22.7% | 97.4% | 61.5% |
| | Medium Gaussian | 81.4% | 22.2% | 97.8% | 63.3% |
| | Coarse Gaussian | 79.2% | 0.0% | 99.6% | 64.1% |
| | Fine KNN | 72.0% | 29.2% | 83.5% | 60.4% |
| | Medium KNN | 80.5% | 28.1% | 95.2% | 62.8% |
| | Coarse KNN | 80.0% | 8.7% | 99.2% | 61.0% |
| | Cosine KNN | 80.3% | 27.2% | 95.1% | 62.9% |
| | Cubic KNN | 80.5% | 28.0% | 95.2% | 62.8% |

* TP (1): True Positive for electricity.
 ** TP (2): True Positive for natural gas.
 ***TP (3): True Positive for heating oil.

to be the PDF for the thermostat on/off model for each condition, and the normal distribution was modeled to estimate the setpoints.

4. Design of simulation: Central okanagan region

4.1. Energy simulation in energyplus

Fig. 6 presents a schematic of the SDD while surrounded by two other buildings. Notably, the effect of the adjacent buildings is considered in

the EnergyPlus simulation, given the shadow they project on the studied SDD. The SDD has an area of approximately 200 m², and it consists of a ground floor with a gable-type roof. The building has three bedrooms and two bathrooms. It was designed using BEopt software (Fazli, Yeap & Stephens, 2015), and we extracted the IDF file to connect it through EnergyPlus.

To simulate energy consumption due to the use of equipment, we assumed that different IH activities were associated with the use of relevant equipment. For example, the HPM activity was assumed to involve the use of the following appliances: washing (500 W) and drying machine (2000 W), dishwasher (1300 W), vacuum cleaner (1600 W), and iron (1100 W). The LDA activities were assumed to involve the use of TV (220 W) and video games (90 W), whereas the MAND involved the use of laptops (140 W) and an office lamp (50 W).

4.2. Design of alternative scenarios

We have tested the model for three scenarios: before, during, and after the COVID-19 pandemic. It is important to mention that we do not intend to confine the temporal COVID-19 stages (i.e., before, during, and after) with specific dates. At the time that we are writing this manuscript, COVID-19 continues to spread in Canada and around the world. These temporal stages represent a typical day before, during, and after the lockdown given available records from the literature. Specifically, the “before COVID-19” represent the period before the emerging of the virus and how the individual’s IH. and OH. behaviors were. The “during COVID-19” period represents the time right after the imposed lockdown, and shows how travel and in-home behavior have changed. The “post COVID-19” period represents a future state where the lockdown restrictions will be eased and life will return to normal. The main controlling factor in these three scenarios is the total IH and OH duration. According to a study by Fatmi et al. (2021) for the Central Okanagan region, the OH duration was found to be dropped by approximately 50% during the COVID-19 pandemic (Fatmi et al., 2021). Therefore, we adopted this distribution to adjust the OH and IH activity durations for alternative scenarios during the pandemic accordingly. Note that the

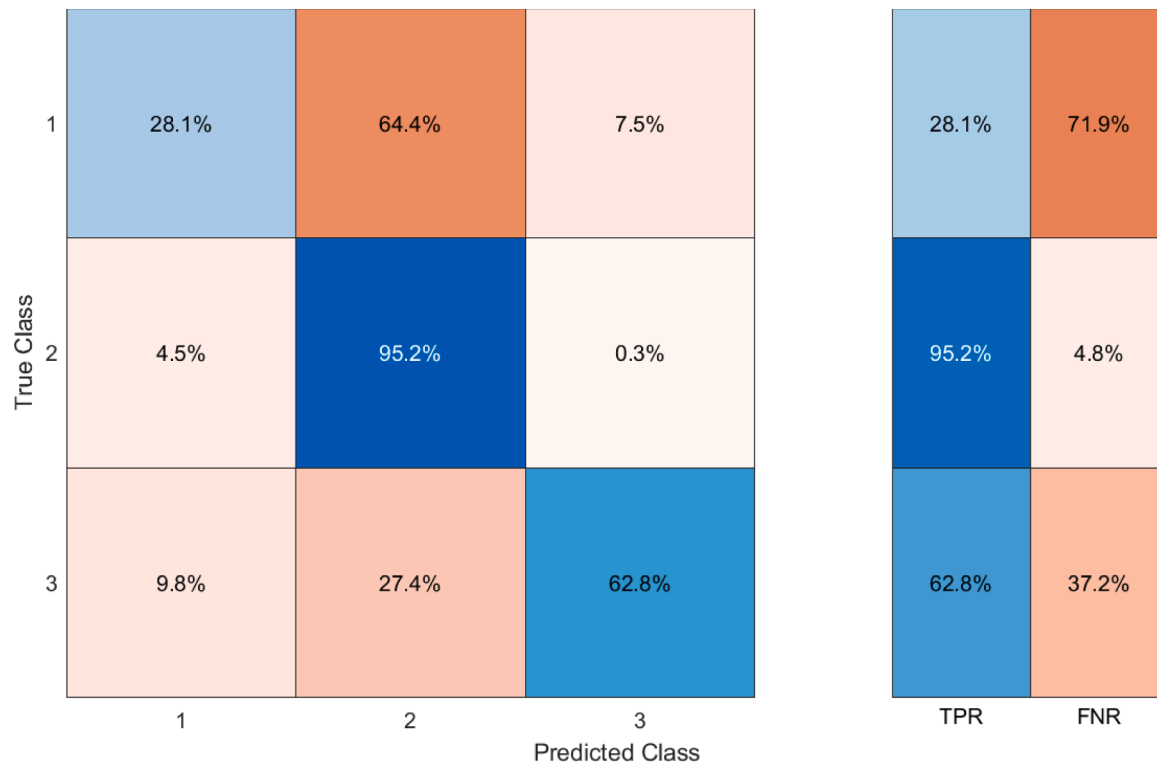


Fig. 5. Confusion Matrix of SoE Ensemble Trees Model.

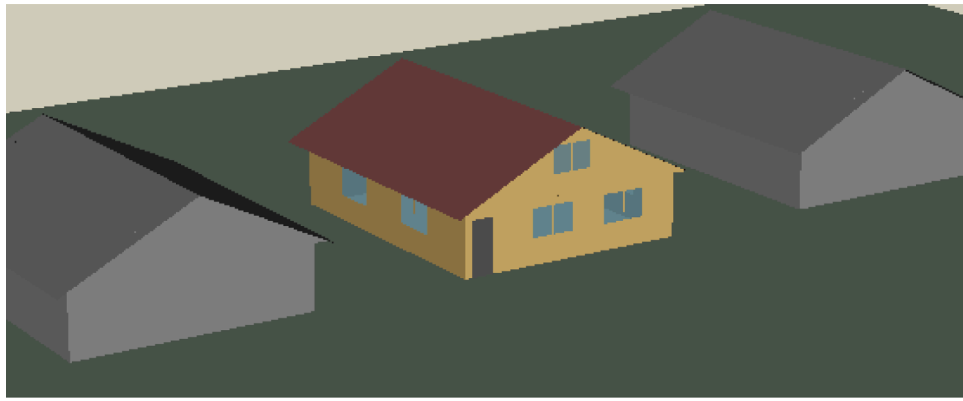


Fig. 6. Schematic of a Single Detached Dwelling.

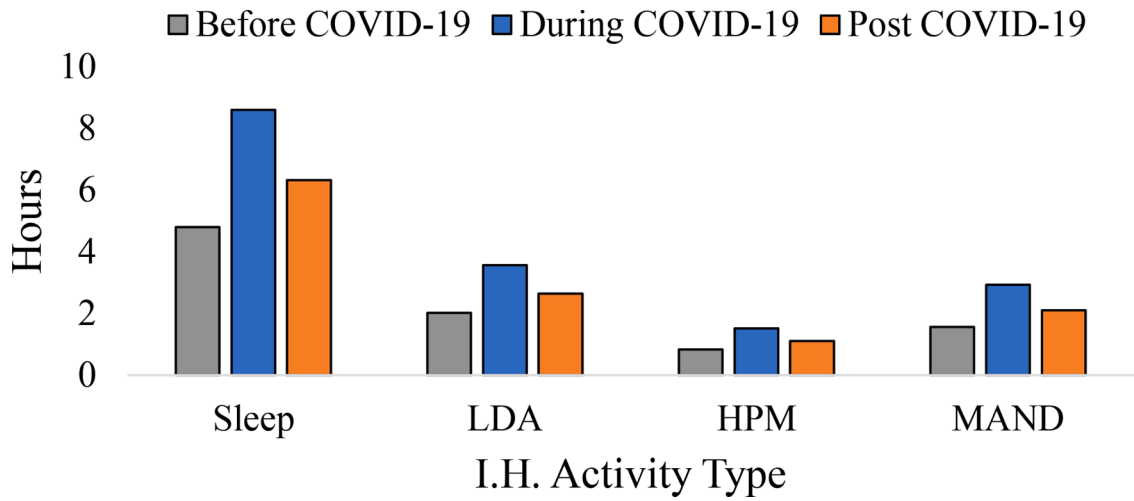


Fig. 7. IHD of individuals with respect to COVID-19 pandemic.

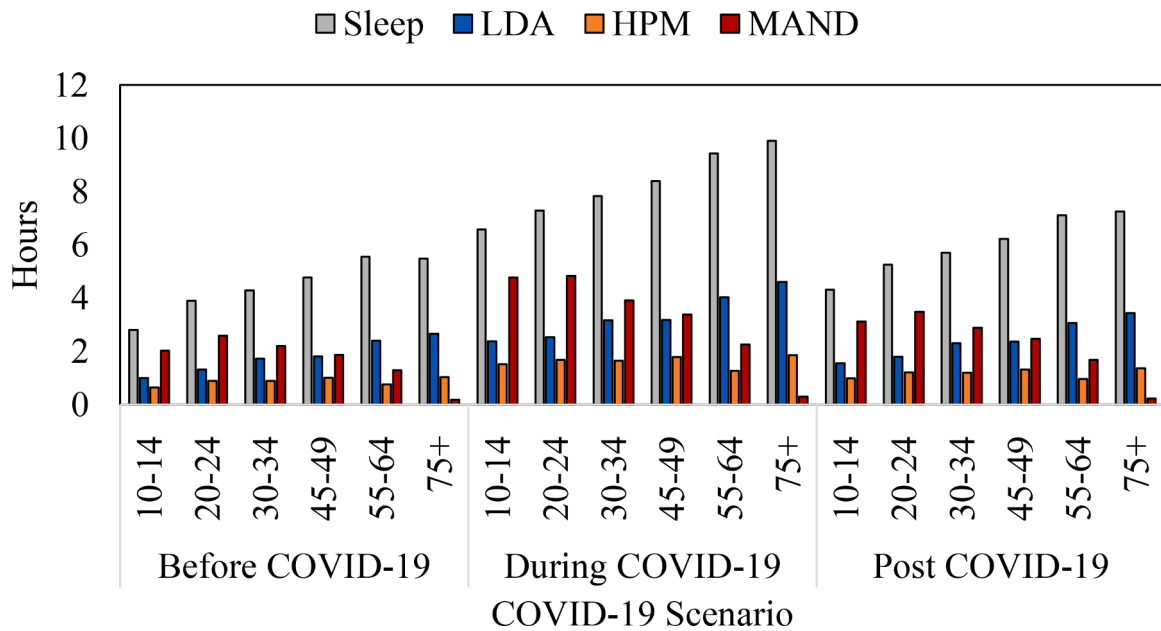


Fig. 8. IHD versus Age Group.

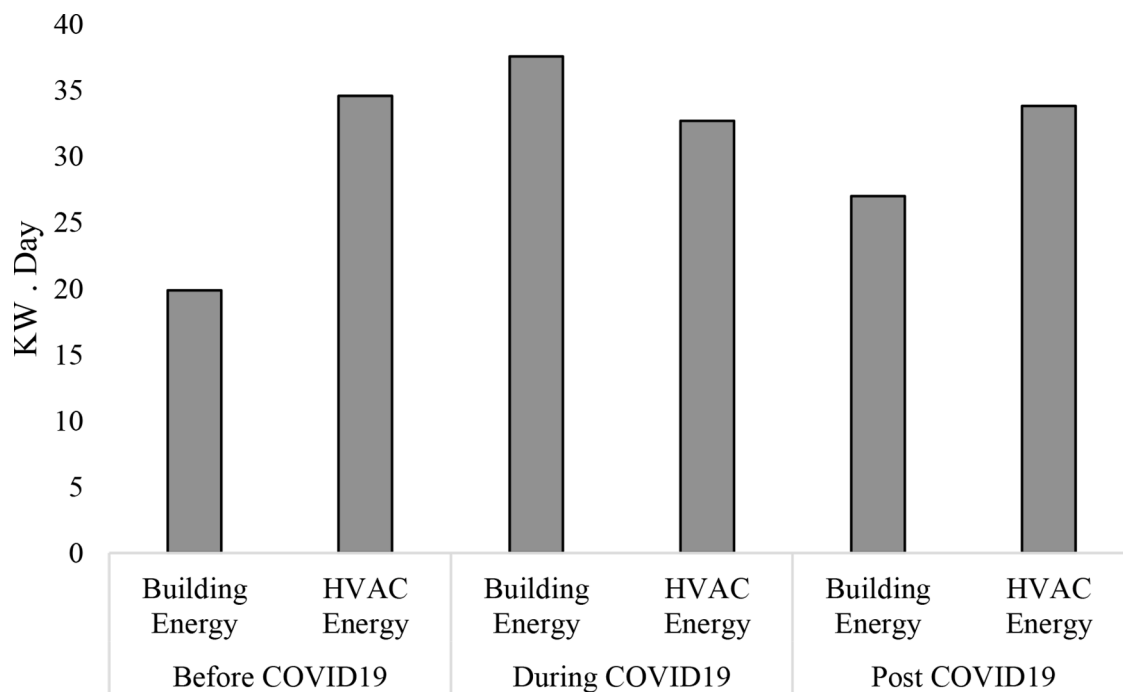


FIG. 9. Overall Energy Consumption of Single Detached Dwelling in Okanagan Region.

“during COVID-19” scenario represents the timepoint of March to April of 2020, which was immediately after the COVID-19 restrictions, social distancing, and business closures were deployed in Canada. For the post-COVID-19 scenario, we assumed that the OH duration would be recovered by approximately 80% compared to the “before COVID-19” era. As the IH activities and their duration differ for each individual, the energy consumption changes accordingly. This analysis is important to have a deeper understanding of the disaggregated energy consumption in a household. This could open newer dimensions in saving energy based on occupants’ behavior and not only the efficiency of appliances.

5. Results and discussions

The purpose of this section is to present the outcomes of the agent-based simulation model and predict the residential energy consumption for the Central Okanagan region for the three COVID-19-related scenarios described above. The runtime for each simulation scenario took approximately 48 h on a computer with 32 GB of RAM and Intel Xeon 3.40 GHz processor. This section aims to answer the following questions:

- 1 How did the residential energy consumption change due to the COVID-19 restrictions? How is it expected to be long after the pandemic?

Table 4
Test of Statistical Significance of Energy Consumption Difference during COVID-19 Periods.

| Period | Energy Type | F-value | F-critical Value | P-value |
|-------------------------------------|-----------------|----------|------------------|-----------|
| During COVID-19 vs. Before COVID-19 | Building Energy | 0.288274 | 0.984298 | 0 |
| | HVAC Energy | 1.10688 | 1.015952 | 2.49E-26 |
| Post COVID-19 vs. Before COVID-19 | Building Energy | 0.56951 | 0.984298 | 0 |
| | HVAC Energy | 1.042389 | 1.015952 | 7.995E-06 |

- 2 What is the geospatial change in residential energy consumption across the Central Okanagan region?
- 3 What is the relationship between in-home activity and residential energy consumption?

Before answering the aforementioned questions, we will discuss the predicted IHD of individuals before, during, and long after the pandemic (Fig. 8). As expected, the IHD is predicted to increase during the pandemic among all types. The increase is as follows: 79%, 76%, 81%, and 87% for sleep, LDA, HPM, and MAND, respectively. After the pandemic, it is expected that individuals will adjust their activities back to normal, but some changes might occur to their lifestyles given the accumulated experiences of activities such as remote working, home-schooling, and online shopping and exercises. Our trained models were fed on this fact, given that out-of-home duration will recover by approximately 20%–25% from the pre-pandemic situation. Accordingly, it is predicted that IHD in the post-COVID-19 era will be lower than that during but slightly higher than that before the pandemic.

Fig. 8 shows the IHD versus age groups where the sleep and LDA activity durations are predicted to increase with the age group. In other words, the sleep and LDA durations of the older age groups are predicted to be higher than those of the younger age groups. By contrast, the durations of the HPM and MAND activities are predicted to be higher for the younger age groups compared with their older counterparts. Regarding the effect of the pandemic, the duration of all in-home activities is predicted to increase for all age groups during the pandemic and partially recover long after.

To answer the first key question, we analyze the overall energy consumption of the Central Okanagan region in the three considered scenarios (Fig. 9). Two energy measures are presented: building energy (i.e., lighting and appliances) and HVAC energy (i.e., heating, ventilation, and air conditioning). As the simulation was conducted for a winter day, the HVAC energy consumption was expectedly predicted to surpass the building energy before and after the pandemic. However, during the pandemic, the building energy seemed to slightly surpass the HVAC energy (X Zhang et al., 2020.). As both energies (building and HVAC) were connected to the time spent in-home, the “during COVID-19” scenario exhibited a higher energy consumption by 29% compared with

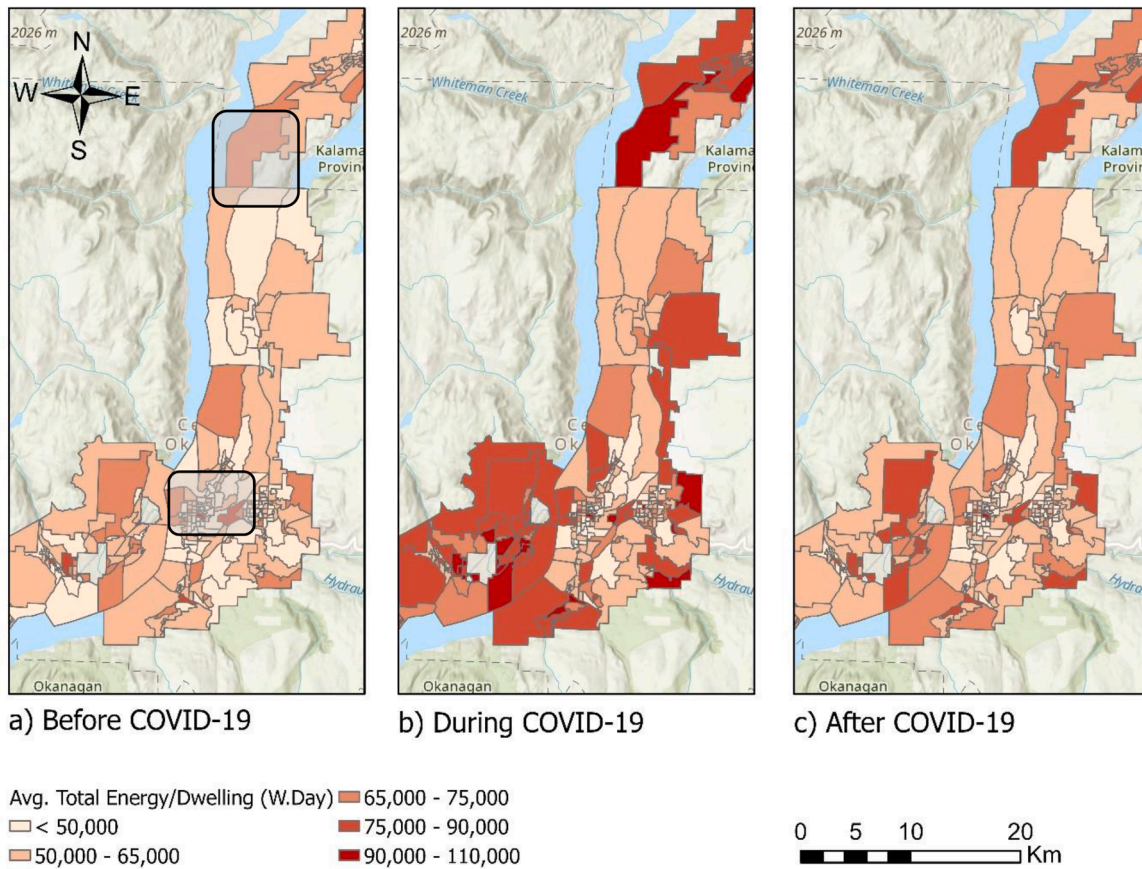


Fig. 10. Geospatial Distribution of Total Energy Consumption per Dwelling in Okanagan Region.

the “before COVID-19” scenario. Similarly, the energy consumption is predicted to be lower for the “post-COVID-19” compared to the “during COVID-19” as individuals are simulated to spend less time in-home.

The F-test was conducted to assess the statistical difference of the energy consumption across the three periods Table 4. shows the F-value, F-critical value, and P-value for the building energy and HVAC energy of the during and post COVID-19 conditions compared with those before the pandemic. Clearly, the building energy at both during and post-COVID-19 were statistically different that before the pandemic. On the one hand, the results of the HVAC energy did not show any major statistical difference across the COVID-19 periods. This result was also noticeable from Fig. 9 as the HVAC energy consumption was relatively flat across the periods. This result indicates that using HVAC did not significantly change during the pandemic compared with before the pandemic. It would be interesting to further investigate this observation by conducting a separate questionnaire that was distributed to locals in the study area.

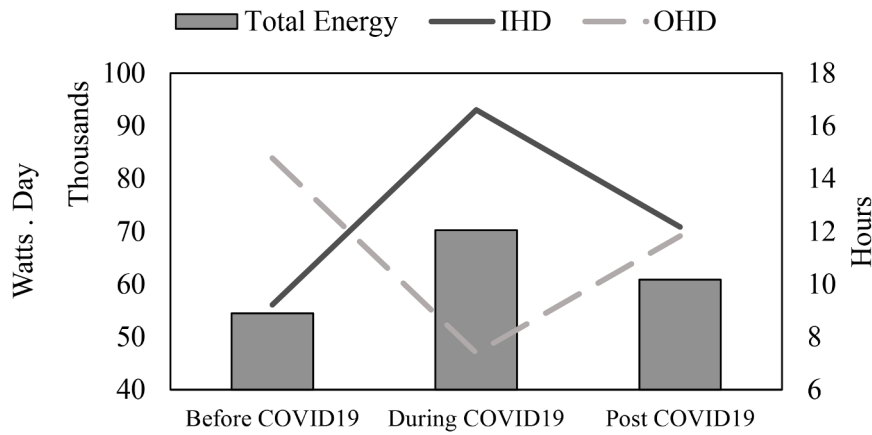
Regarding the second key question, we need to understand the geospatial distribution of the energy consumption. For this purpose, we generated heat maps representing the total energy consumption per dwelling at the dissemination area (DA) level for the Central Okanagan region (Fig. 10). As shown, Fig. 10-a illustrates the pre-COVID-19 era, where the energy consumption per dwelling was predicted in the range of 50–75 kWh per day. Interestingly, a lower energy consumption was predicted for the urban centers of the region compared with the surrounding suburban and rural areas (the shaded areas indicate examples for one urban center and another rural area). The reason is that this study focuses on single-detached dwellings only, which are prevalent in suburban and rural areas. At the northeast and southwest of the study area, a moderate energy consumption per dwelling of approximately 50–75 kWh per day was predicted. For the COVID-19 scenario, high

energy consumption per dwelling was recorded at suburban and rural DAs (Fig. 10-b). However, the urban center of Kelowna city does not show substantial differences in energy consumption at the DA level. In the post-COVID-19 era (Fig. 10-c), a lower energy consumption was predicted for the suburban and rural DAs than during the COVID-19 era. However, it was slightly higher than before the pandemic. In summary, the energy consumption of dwellings increased during the COVID-19 era by approximately 29%, mostly in the suburban and rural areas with respect to single detached dwellings.

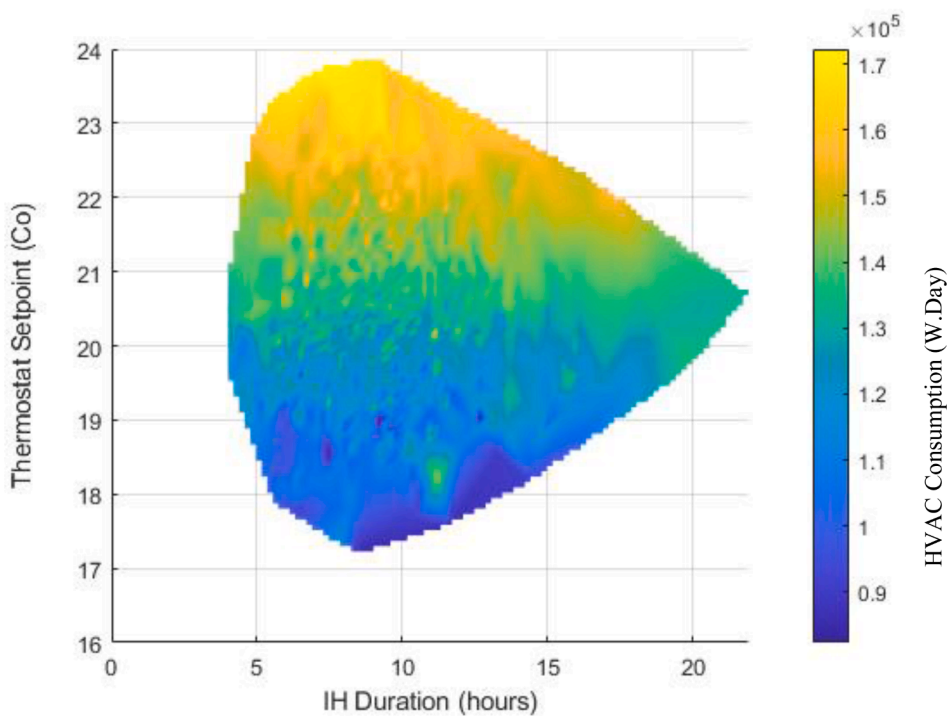
Finally, we analyze IHD and energy consumption to answer the third question. As shown in Fig. 11-a, the daily average IHD increased from approximately 9 h/day to 16.5 h/day during the pandemic. Accordingly, this resulted in higher energy consumption by 79%. In the example in Fig. 11-b, we can observe a 3D mesh plot of in-home duration, thermostat setpoint, and energy consumption for dwellings with electric baseboards. As the simulation was completed in winter at low IH duration and low thermostat setpoint, the HVAC energy consumption was recorded at its minimum levels. The HVAC energy gradually increased with the increase of IH duration and thermostat setpoint, but the influence of the thermostat setpoint appeared to be higher than the IH duration (the highest HVAC energy consumption was recorded at the most severe thermostat setpoint (setpoint at 23.5 °C and IH of approximately 10 h). One of the key takeaways from Fig. 11-b is the importance of implementing an efficient thermostat setpoint given the surrounding conditions to mitigate excessive energy consumption.

6. Conclusion

In this study, we developed a hybrid framework consisting of an agent-based energy simulation coupled with ML models to simulate the residential energy consumption of an urban region. The proposed



a) Total Energy Consumption versus IH and OH duration



b) 3D Plot of IHD, Thermostat Setpoint, and Energy Consumption of Dwellings with MHE of Electric Baseboard

Fig. 11. Relationship between IHD, OHD, and Total Energy Consumption; a) Total Energy Consumption versus IH and OH duration, b) 3D Plot of IHD, Thermostat Setpoint, and Energy Consumption of Dwellings with MHE of Electric Baseboard.

framework included ML modeling of the following components: in-home and out-of-home activity duration, heating equipment, and source of energy. Additionally, probabilistic models to estimate the thermostat setpoint were developed at different conditions. Finally, we simulated the residential energy consumption for three scenarios related to the pandemic, i.e., before, during, and after. The presented framework is part of a large-scale agent-based integrated urban model (IUM) currently under development at The University of British Columbia. Typically, IUM intends to simulate the evolution of urban systems given the influence of residential and job locations, employment records, demographic and social characteristics, and others. Furthermore, IUM relates the evolution in urban systems to the transportation demand where eventually policies related to the built environment could be tested and their implications on both urban and transportation systems could be estimated. Our proposed framework extends the application of

conventional IUMs toward predicting detailed urban energy use by adequately representing occupants' activity behavior and consequently improving the forecasting accuracy of energy use.

The contributions of this study are the following: 1) integrating ML techniques with agent-based simulation to predict the regional residential energy consumption, 2) integrating individual occupants' behavior while simulating urban energy, and 3) developing and testing novel scenarios to predict how residential energy consumption evolves from pre- to during- to post-pandemic.

To illustrate the capabilities of our proposed framework, we implemented a full-scale simulation for the Okanagan region, BC, in Canada. The case study was limited to 24 h of a typical weekday during the winter season and only for single detached dwellings. The key outcomes of this study are summarized as follows:

- High-accuracy ML models were developed to predict the state and properties, such as main heating equipment, of agents in the study area.
- The IHD during the pandemic was predicted to increase by approximately 80%, where some differences were predicted between age groups. It is predicted that IHD after the pandemic will partially recover (i.e., by 32%) compared with the pre-COVID-19 situation.
- Similarly, the energy consumption was predicted to increase by 29% during the pandemic, and the energy loading increased by 89%. At the dissemination area level, the substantial increases in energy use was predicted in the suburban areas because single detached dwellings were prevalent in those neighborhoods.
- Generally, as the in-home duration increased, the energy consumption of the dwelling was predicted to increase independently of the thermostat setpoints (i.e., high temperature in winter).

In future studies, we aim to improve the IH and OH components by implementing a full-scale activity-based travel model using econometric techniques and comparing them with the developed ML models. Moreover, we plan to extend the simulation in this study to include demographic simulator, and transportation systems simulation in addition to the residential sector. Furthermore, other dwelling types are planned to be included to the simulation of the residential sector, such as town houses and condos. From a different perspective, the framework in this study could be utilized to assess the variations in environmental emissions given the changes in residential energy consumption at different lockdown stages. Another goal is to upgrade the existing model into a comprehensive energy assessment tool that not only considers the residential energy consumption but also accounts for the transportation-related energy consumption of households. Additionally, we plan to investigate the possibility of running our framework in a parallel computing environment to reduce its running time.

The outcomes of this research could be utilized to assess the environmental impacts of various emerging transportation and land use-related policies such as work from home strategies. This is important as work-from-home strategies could reduce out-of-home activities and consequent travel-related emissions and energy consumption (Milojevic-Dupont & Creutzig, 2021). On the other hand, this study demonstrates that such strategy is likely to increase energy consumption at-home, indicating a need to adopt a holistic modeling approach incorporating the adjustment in both travel and in-home activities while assessing the impacts of transport and land use policies. This study also demonstrates the need for disaggregate-level such as agent-based modeling techniques to accommodate the changes in individuals' daily activities at-home and their consequent impacts on the urban environment. Such bottom-up holistic approach is expected to yield higher accuracy results of energy consumption and assist in testing policies more effectively. The results related to the increase in residential energy consumption also refers to a disproportionate shift of the energy cost burden – i.e., from the employer to the employees. This finding indicates the need for equity consideration while cities and employers evaluate the potential for adopting the work-from-home strategy. Furthermore, as cities are aggressively investing to improve their sustainability through reducing their energy consumption, the developed tool can be used to assess various environmental challenges including urban heat island and climate change to develop sustainable cities and societies.

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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