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Assessing the impact of occupant behavior on residential building performance: A case study of window operation

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HIGHLIGHTS

- Occupant-specific window opening/closing models are learned from multi-winter data.
- Twelve logistic regression models capture heterogeneity across different occupants.
- Closed-loop IDA ICE co-simulation quantifies occupant behavior impact on energy use.
- Normalized energy-increase metric benchmarks against a closed-window baseline.
- Window operation can raise residential space-heating energy use up to threefold.

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ABSTRACT

Occupant–building interactions significantly influence indoor environmental quality and energy use, yet they are still often represented in building energy simulation with simplified or schedule-based assumptions. This study quantifies how occupant-specific (heterogeneous) window-opening and window-closing behavior affects space heating energy use in a Swedish residential building under comparable conditions. Using four winters of monitored data from several single-occupant apartments, occupant-specific logistic regression models are developed for window opening and closing actions. It is shown that common drivers (e.g., indoor air quality and time of day) coexist with substantial inter-occupant differences. These models are then integrated into a closed-loop co-simulation (IDA ICE–MATLAB) with a calibrated building model to compare occupant profiles under identical boundary conditions and against a consistent closed-window reference case. Impacts are reported as a normalized heating energy increase relative to the closed-window case, providing a direct comparison across occupant profiles and different scenarios. The results show that window operation can lead to large and highly variable heating losses, with some occupant profiles increasing space heating energy use by up to threefold relative to the closed-window baseline. These findings demonstrate that representing inter-occupant heterogeneity is essential for reliable energy performance assessment and occupant-centric building control design.

1. Introduction

Buildings in the European Union account for about 40% of the total final energy consumption and 36% of greenhouse gas emissions [1]. Heating, ventilation, and air conditioning (HVAC) systems are essential for maintaining indoor comfort, but are also among the largest energy consumers [2]. Occupant behavior is recognized as a key factor in building energy performance, particularly in relation to HVAC operation [3,4]. This perspective has motivated the view of modern buildings as cyber-physical-human systems (CPHS). CPHS is an emerging interdisciplinary area that addresses the dynamic and complex interactions between cyber-physical systems (namely, integrated systems that combine physical systems with computational devices) and humans [5, Chapter 4]. Due to the bidirectional, coupled, closed-loop interactions between the physical environment and conditions, sensors and actuation devices, optimization and control paradigms, and building occupants, modern buildings provide a representative example of CPHS. Yet traditional analyses often oversimplify these interactions, treating occupants as passive rather than active participants [6].

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Within this context, window operation has gained increasing attention because it directly affects both indoor climate and energy consumption [7–10]. Existing studies on window operation behaviors can be broadly categorized by the modeling approaches employed, such as logistic regression [11–13], Markov processes [12,14], and deep learning techniques [15], and by the type of building analyzed [7,8,15–17]. A comprehensive analysis of window operation behavior is presented in [18], which categorized various modeling techniques based on their complexity, implementation level, and data requirements, with logistic regression identified as one of the most commonly used models. While most prior studies focused on office buildings [3,15,19–21], growing attention has been given to analyzing occupant behavior within residential buildings in relation to physical environmental drivers [9,22,23]. For instance, [24] identified time of day, CO_2 concentration, and average outside temperature as key drivers of window operation in German households. Although research on residential buildings has primarily focused on multi-occupancy settings, [9] used logistic regression to model window operation behavior in a Swedish residential building with four occupants living in separate studio apartments. The study concluded that while common factors, such as air quality and time of day, influenced all occupants, individual variability existed in the key drivers of window operation behavior.

The considerable variability of occupant behaviors contributes to discrepancies between predicted and actual building performance, known as the energy performance gap [25]. Previous research has therefore examined the energy impact of window-opening behavior, but much of this work emphasized office buildings and cooling energy, often in the context of natural ventilation and cooling energy savings [19,26–28]. Integration of occupant behavior models into building energy simulation (BES) tools (e.g., EnergyPlus [29,30] and IDA ICE [31,32]) has been studied; however, comparatively fewer studies focus on residential settings and use occupant-specific window-operation models to quantify heating energy impacts beyond schedule-based assumptions. Addressing this gap is relevant as aggregated representations fail to capture inter-occupant heterogeneity and can therefore misrepresent both the typical heating loss and the range of heating energy impacts between occupants. As a result, the heating energy variation caused solely by differences in occupants' window operation is still not well quantified under controlled, comparable conditions. Building testbeds support such analysis by allowing high-resolution monitoring of indoor conditions and occupant interaction [33–36]. For example, [37] reported high sensitivity of heating demand to window-opening actions in a multi-residential building, and [38] showed that window-opening behavior predicted from monitored data, when implemented in EnergyPlus, can lead to considerable heating-season energy losses in dormitory buildings. However, these studies typically represent window-operation behavior at an aggregated level (e.g., one profile per dwelling or building) and therefore do not quantify how much the heating energy impact can vary across individual occupants. These findings motivate approaches that use measured occupant data to represent occupant-specific (heterogeneous) window-operation behavior and quantify its heating energy impact under comparable conditions.

*Contributions.*This paper quantifies how occupant-specific window-opening and window-closing behavior affects space-heating energy use in a residential building under controlled, comparable conditions. We derive window-operation models from multi-winter measurements and evaluate them in a closed-loop IDA ICE–MATLAB co-simulation using a calibrated model of the Testbed KTH. This setup provides a controlled comparison across occupant profiles under identical boundary conditions (e.g., weather conditions and building/HVAC operating settings) and benchmarking against a consistent closed-window reference case, so that differences in heating energy use are driven by window-operation behavior rather than by other influencing factors. In particular, the main contributions are: (i) Preserving occupant-specific heterogeneity in window operation: We develop separate window-opening and window-closing models for each occupant (twelve logistic regression models in total) using collected data from the KTH Live-In Lab in Stockholm, Sweden, (ii) Controlled scenario-based energy impact assessment in a real case study: We implement a closed-loop simulation setup in which window actions respond to simulated indoor/outdoor conditions rather than fixed schedules, for direct comparison across occupant profiles under identical boundary conditions, and (iii) Quantifying the magnitude of impacts: We introduce a normalized heating energy increase metric relative to a closed-window baseline, which yields a clear interpretation and comparison across occupant profiles and scenarios. Using this indicator, we show that window operation can increase heating energy use by up to threefold compared with the baseline.

Outline. The paper is organized as follows: Section 2 provides an overview of the building's physical and digital representations. Section 3 details the experimental dataset collected from the KTH Live-In Lab. The proposed approach for analyzing the impact of different occupant behavior profiles on space heating energy consumption is outlined in Section 4. Section 5 presents the simulation results and discusses potential future directions. Finally, Section 6 offers conclusive remarks.

2. Experimental setup

This section introduces the building environments utilized in this study: the KTH Live-In Lab and Testbed KTH (Section 2.1), the simulation environment, IDA ICE, used to develop a digital model of the building (Section 2.2), and the IDA ICE–MATLAB co-simulation environment (Section 2.3), which is employed to assess the impact of different occupant behavior profiles on the total space-heating energy consumption in the Testbed KTH model.

2.1. Building testbed: the KTH live-in lab

The KTH Live-In Lab[1] features a variety of building testbeds, including student housing and lecture halls [35]. One of these testbeds, Testbed KTH, is the focus of this study. The KTH Live-In Lab represents a CPHS, including an extensive sensor network, a redesignable testbed layout, and advanced interaction capabilities with its occupants.

Sensor data collected from these testbeds are stored and shared via the KTH Live-In Lab datapool (Fig. 1(a)). The KTH Live-In Lab utilizes advanced sensing technologies to monitor indoor environmental parameters, including indoor temperature, relative humidity, CO_2 concentration, and volatile organic compounds, and to measure the resources used in the apartments for space heating and domestic hot water production. Additional magnetic sensors detect windows and door status (open, closed), while motion sensors detect occupancy. Indoor thermal comfort and air quality are controlled via a ventilation system equipped with an air-handling unit (AHU), featuring dedicated distribution outlets for each apartment (Fig. 1(g)). This arrangement enables building managers to precisely control heating and air quality settings, while occupants can only adjust the heating setpoint temperature. For more detailed information, refer to [35,39].

The Testbed KTH covers a total floor area of 300 m^2 (Fig. 1(b) and (c)). Additionally, the layout can be redesigned (Fig. 1(d)–(f)). To maintain consistent terminology across these reconfigurable layouts, ranging from full apartments (Fig. 1(d)) to private rooms with shared facilities (Fig. 1(f)), we use the term *apartment* throughout the paper to refer to each residential unit in the testbed.

The Testbed KTH accommodates undergraduate students (of comparable age) from the KTH Royal Institute of Technology who live there full-time. Each apartment is typically rented to a single occupant, regardless of the layout, with one apartment being rented out to one or two occupants.

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[1] liveinlab.kth.se/en.

Fig. 1. (a): Diagram illustrating the KTH Live-In Lab data infrastructure. (b): Exterior view of the Testbed KTH. (c): Sectional illustration of the Testbed KTH. (d): The Testbed KTH layout used until June 2020. (e): The Testbed KTH layout used from August 2020 to June 2021. (f): Latest layout of the Testbed KTH. (g): Ventilation system of the latest layout. The supply and extraction air ducts are denoted by red and yellow colours, respectively. Image sources: liveinlab.kth.se/en/data-infrastructure, liveinlab.kth.se/en/datapool/testbed-infrastructure (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

2.2. IDA ICE building simulation environment

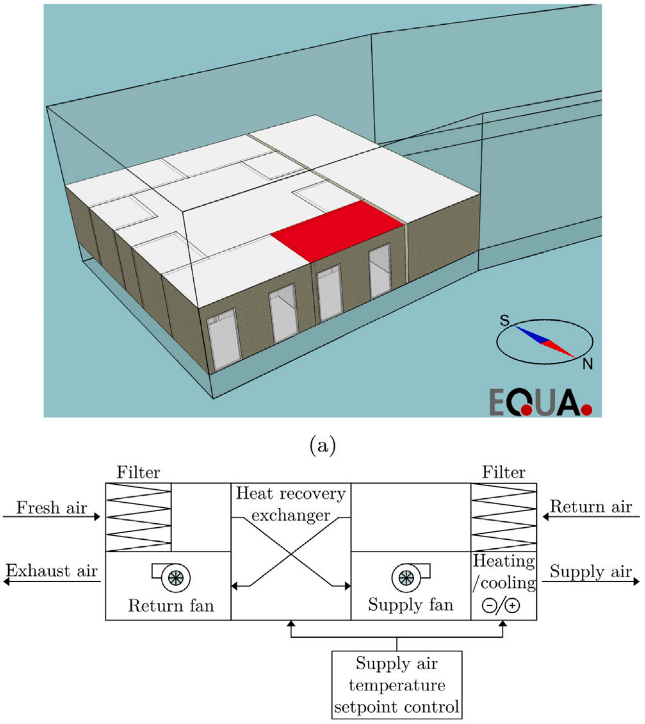
IDA ICE simulation software is an advanced and dynamic multi-zone simulation tool designed to accurately model buildings, their systems (such as HVAC systems and heat pumps), and controllers. It replicates the thermal dynamics and indoor air quality and calculates the energy consumption of buildings [40]. IDA ICE simulation tool has been validated according to EN 15255-2007, demonstrating performance within specified error boundaries (0.5 °C for operative temperature and 5% for maximum and average cooling power) in all but one test case. Moreover, validation scores according to EN 15265 are rated as "A" in most heating cases [41].

A building model reflecting the Testbed KTH layout, implemented from August 2020 to June 2021 (Fig. 1(e)) has been developed and calibrated in IDA ICE 4.8 (Fig. 2(a)) [42]. The primary zone parameters required for calculating heating energy in IDA ICE are detailed in Table 1. The supply airflow to each zone is controlled by a variable air volume (VAV) strategy. Therefore, the effective ventilation rate is time-varying rather than a single fixed value. In the calibrated IDA ICE model, the zone supply airflow is bounded between 0.3 and 7 L/sm^2. A slightly higher upper bound reflects that the Testbed KTH is operated as an all-air system; no radiators are used in the apartments to support flexible reconfiguration of the apartment layouts while maintaining comfort through air-based heating [35]. In addition to the thermal properties of the building envelope, it is necessary to include internal heat gains in the heating energy calculations. Internal heat gains are generated by occupants' metabolic activities, the use of electrical devices, and thermal emissions from artificial lighting. Detailed information regarding internal gains, including the rated input and operational schedules for lighting, as well as the activity level and presence of occupants, is provided in Table 2.

Occupancy in IDA ICE can be represented using a time-dependent schedule that specifies the number of occupants over time. In this study, we adopt a controlled assumption of constant occupancy presence in the analyzed zone (Table 2). This choice isolates the energy impact of window operation from uncertainties in presence patterns, while preserving time of day effects in the behavior models (Section 3).

To enhance model accuracy, the simulation model features a separate zone per room of the apartments. In this study, we focus on a single zone (living room/bedroom), as detailed later and highlighted in red in Fig. 2(a), to allow for a direct comparison of energy impacts of occupant-driven window operation with a baseline scenario.

The heating and ventilation systems are provided by balanced mechanical ventilation with heat recovery. Fig. 2(b) illustrates a simplified



(a)

(b)

Fig. 2. (a) Model of the Testbed KTH in IDA ICE. The red-highlighted zone is considered for the numerical analysis, and (b) simplified schematic representation of the AHU as modeled in IDA ICE (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

Table 1
Building envelope and system parameters corresponding to the simulated zone in IDA ICE.

Building components	Building parameters		
	Name	Unit	Value
External walls	U-value	W/m^{2}K	0.18
Windows	U-value	W/m^{2}K	1.46
	Surface	m^2	2.11
	Solar heat gain coefficient	–	0.61
Ventilation	Heat recovery efficiency	–	0.6
Air infiltration	Air changes per hour	ACH	0.5 at 50 Pa

Table 2
Summary of internal heat gain sources, including occupant activity and lighting schedules in IDA ICE.

Internal heat gain sources	Details	Value	Schedule
Occupancy	activity level [MET][*]	1	One occupant always present
Light	rated input [W]	50	0 between 8 and 15; 0.5 between 15 and 17; 1 otherwise.

[*] MET: metabolic equivalent of task.

scheme of the AHU in IDA ICE, where the supply air temperature setpoint can be configured as a constant value, according to a time schedule, or as a function of the outside temperature. The quantity and temperature of the air distributed to each zone are optimized through VAV systems. Specifically, proportional-integral (PI) controllers are employed to maintain the indoor temperature at a user-defined heating setpoint temperature (21 °C in this study) and to ensure indoor air quality by regulating CO_2 concentration.

2.3. IDA ICE–MATLAB co-simulation

BES programs are typically not directly suitable for the design and testing of advanced controllers or the integration of complex occupant behavior models [43]. To address this issue, a co-simulation environment needs to be designed to establish communication bridges between BES programs and control-oriented tools and programming languages, such as MATLAB or Python [44]. The development of an integrated framework linking the IDA ICE simulation environment and MATLAB has been a useful practical contribution of this work. This integration facilitates the use of MATLAB's advanced analytical tools and extensive modeling functionalities. During runtime, IDA ICE exports selected environmental variables, including indoor and outside temperatures, CO_2 concentration, diffuse horizontal irradiance (DHI), and space-heating power to MATLAB at each IDA ICE/MATLAB synchronization step. Pre-developed logistic regression models, trained on real-world data (Section 4), are used within MATLAB to characterize occupant behavior in response to simulated environmental conditions. The resulting window operation signals are then sent back to IDA ICE, enabling the simulation to dynamically reflect occupant-driven window behavior (Fig. 3). To ensure stable and functional co-simulation, a synchronization step of 7.5 minutes is used.

3. Experimental dataset from testbed KTH

The dataset utilized in this study covers the winter season, spanning from October 1 to February 28, for the years 2020 to 2024. This time frame was selected because it corresponds to the Swedish heating season, during which window opening can substantially increase space-heating energy consumption through additional heat losses. This period corresponds to various layouts of the Testbed KTH implemented throughout these years (Fig. 1(e) and (f)), with different groups of occupants holding lease contracts each year. The sensors used in this experimental study are standard commercial devices commonly employed in building applications. These sensors have accuracy levels typical for such use cases [24]; for instance, the indoor and outside temperature sensors have accuracies of ±0.5 °C and ±0.6 °C, respectively. The data was preprocessed before utilization to address discrepancies caused by variations in sensor sampling rates. To address these discrepancies, all variables were synchronized to a common 30-second resolution. Continuous environmental variables were interpolated to this sampling time. For the event-based window-state signal, values at the 30-second sample time were obtained by replacing any gaps with the most recent previously observed state. After preprocessing, the following variables with a sample time of 30 s were considered:

- Window status (open/closed);
- Indoor temperature (T_{indoor}) [°C];
- Carbon dioxide concentration (CO_2) [ppm];
- Diffuse horizontal irradiance (DHI)[W/m^2][2];
- Outside temperature ($T_{outside}$) [°C];
- Relative humidity (RH) [%].

Some of the measured data are illustrated in Fig. 4. Fig. 8(a) shows the distribution of window-opening event durations aggregated across all apartments and four winter seasons. To better reflect occupant-level diversity, we also examined the monitored behavior separately by apartment and winter season. Overall, the number of window-opening actions per day across all occupants typically ranges from 0 to 6 during the winter season. In contrast, window-opening event durations

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[2] The DHI data was obtained from the Copernicus Atmosphere Monitoring Service (CAMS) at: ads.atmosphere.copernicus.eu/datasets/cams-solar-radiation-timeseries?tab=overview.

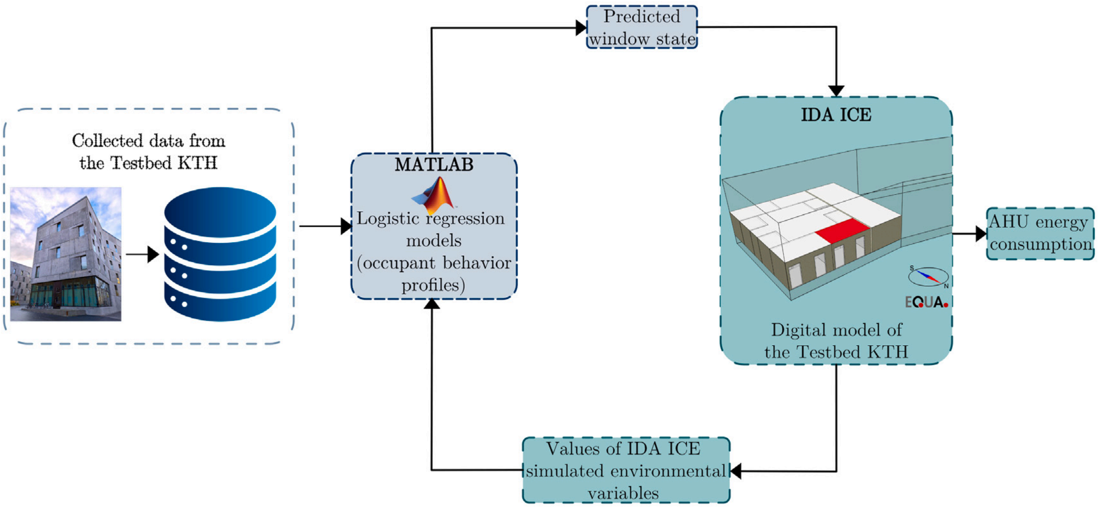

Fig. 3. Co-simulation framework linking IDA ICE and MATLAB for dynamic window operation modeling. At each synchronization step, variables are exchanged between IDA ICE and MATLAB, the occupant model is evaluated, and the window action (opening/closing) is updated. The resulting window command is then held constant until the next synchronization step.

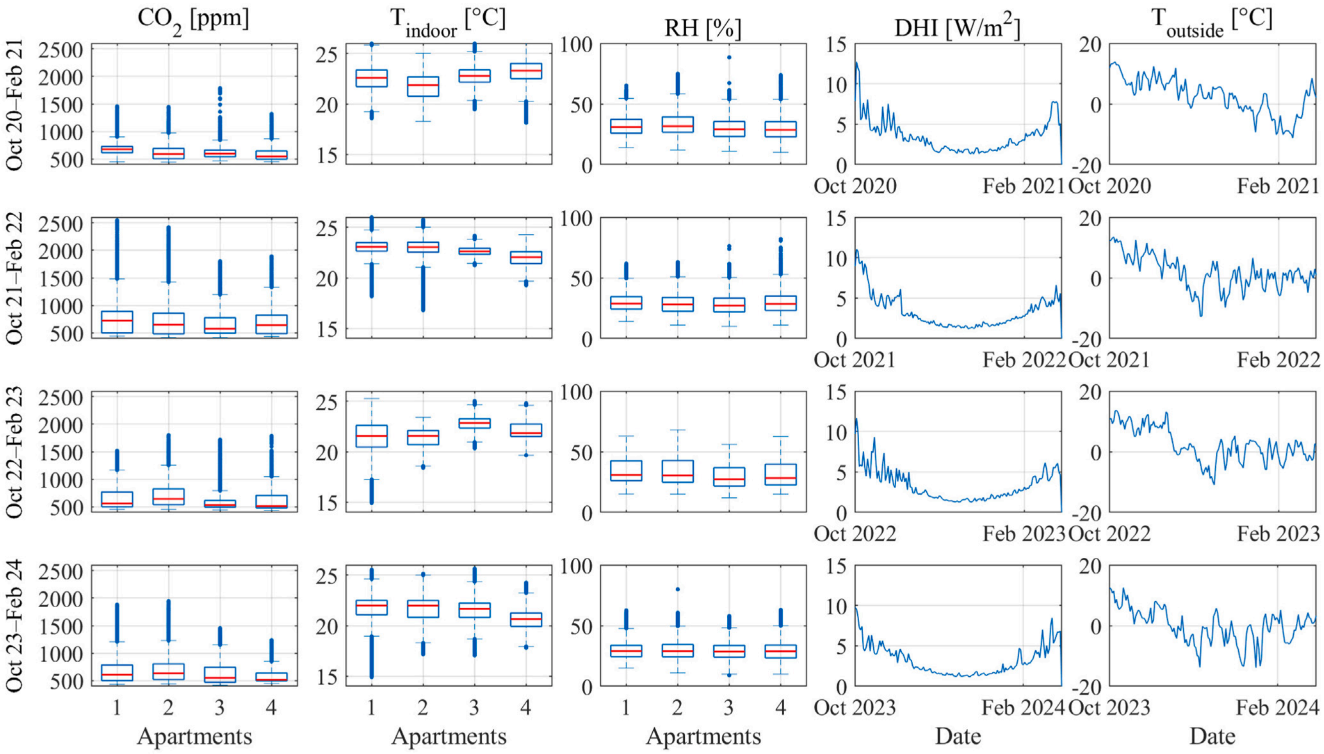

Fig. 4. Some of the monitored data from the Testbed KTH apartments across four periods: October 2020–February 2021, October 2021–February 2022, October 2022–February 2023, and October 2023–February 2024. The boxplots summarize the distributions of the measured parameters: the boxes represent the interquartile range (Q1–Q3), the red line indicates the median, and observations beyond the whiskers are shown as outliers (blue). For improved readability, DHI and T$_{outside}$ are shown as daily averages (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

show substantial variability across apartments and years. For example, Apartment 2 (2021–2022) and Apartment 4 (2023–2024) include some longer opening events (excluding outliers, approximately 10 h and 12 h, respectively).[3]

Based on observations of the window-opening activity in different apartments (Fig. 5), we introduced a categorical variable, denoted by day segment, which groups specific periods throughout the day during which differences in occupants' behavior were most noticeable [9]:

- Day segment 1 (DS1): between 06:00 and 13:00;
- Day segment 2 (DS2): between 13:00 and 22:00;
- Day segment 3 (DS3): between 22:00 and 06:00.

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[3] Detailed apartment- and year-specific distributions of opening-event frequency and duration are provided in the Supplementary Material available at: github.com/MahsaFarjadnia/kth-window-operation-supplementary.

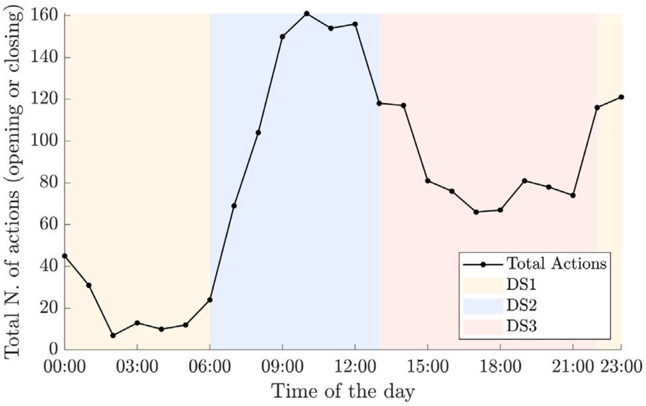

Fig. 5. Total number of window-opening and -closing actions across all apartments over four winter seasons (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

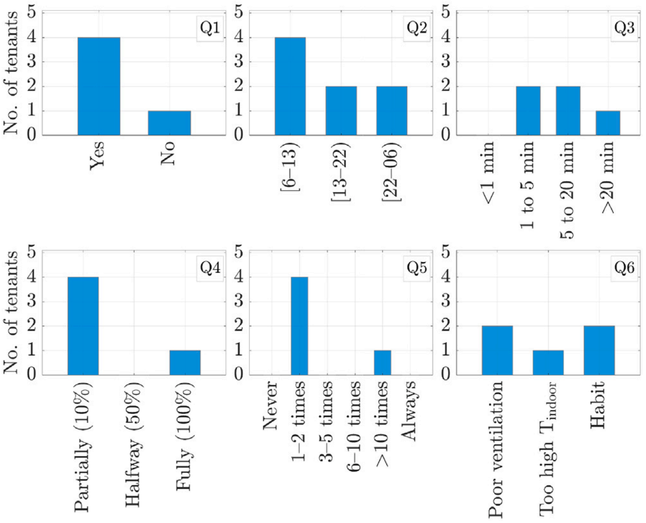

Fig. 6. Survey results from February 2025 among the Testbed KTH occupants. Questions: Q1: Do you usually keep your bedroom door open? Q2: At what time of day do you typically open your windows? Q3: How long do you typically keep the window(s) open? Q4: How much do you typically open the window? Q5: How many times do you open the windows/per day? Q6: Do you have specific reasons for opening the window?.

To complement the sensor-based dataset, a survey was conducted among occupants who resided in the Testbed KTH during the monitoring period to gain insights into their window-opening behavior. Five responses were obtained.[4] While the sample size is limited and may not fully represent all past occupants, the survey aims to gather some understanding of occupants' motivations for interacting with windows (habits versus indoor air quality), their use of space at home, and their behavior regarding window operation (including duration, angle of opening, and time of day). The results are presented here in aggregated form to ensure privacy (Fig. 6). All occupants reported being at home daily and spending most of the daytime (6:00-22:00) in the bedroom, compared to the kitchen and living room. Variability was observed in when occupants opened their windows (morning, afternoon, or night), with a slight preference for mornings, as well as in how long the windows were kept open. One occupant typically kept the windows open for more than 20 minutes (1-2 times daily) due to reported poor indoor air quality (which may also be worsened by keeping their bedroom door closed). Most occupants opened their windows 1–2 times per day, whereas one occupant allegedly opened them more than 10 times daily, citing concerns about poor bedroom ventilation. This "more than 10 times daily" response is interpreted as a qualitative indication of frequent action rather than a precise count. Window opening frequency is quantified from sensor data, whereas the survey is used primarily to describe motivations and typical opening angles, which were not measured through sensors. Almost all occupants open their windows partially (approximately 10% of total opening capacity). The only occupant who fully opens the window (100% opening angle) does so out of habit, once or twice each morning for up to 5 minutes. The survey results align with collected experimental data (Fig. 8; for readability, durations exceeding 24 h are not shown in Fig. 8(a), but they are included in the analysis), which suggests that some occupants keep their windows open for extended periods.

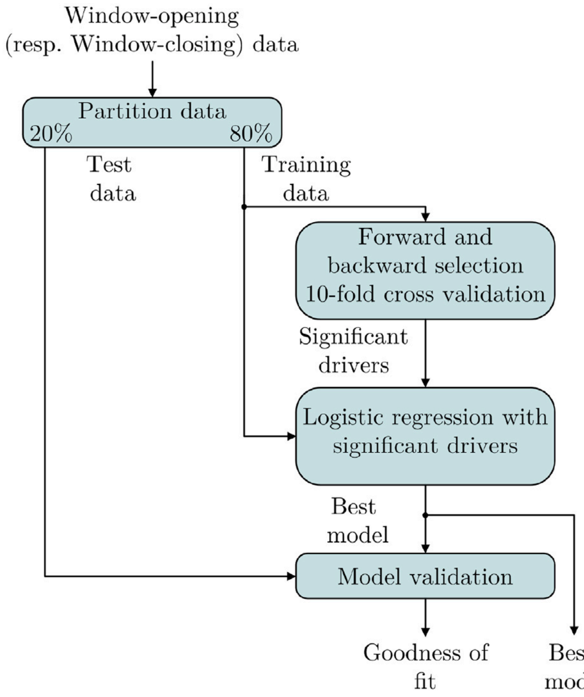

Fig. 7. Diagram of logistic regression model selection and validation procedure. Source: [9].

4. Modeling occupant behavior and energy impact

In this section, first, logistic regression is applied to model occupant window-opening and window-closing behavior, resulting in occupant behavior profiles (Section 4.1). For each occupant, two separate models are developed, one for window-opening and another for window-closing, since the drivers for an opening action may differ from a closing action. These models are trained and validated using experimental data collected from the Testbed KTH (Section 3). Second, these behavior models are used in IDA ICE–MATLAB co-simulation, where two representative winter days are defined to reflect typical and colder-than-average conditions in Stockholm (Section 4.2). Finally, the impact of occupants' window operation behavior on space-heating energy consumption is quantified through a proposed evaluation measure (Section 4.3).

4.1. Logistic regression-based models

Multiple logistic regression was employed to estimate the probability of a window-opening or window-closing action based on a

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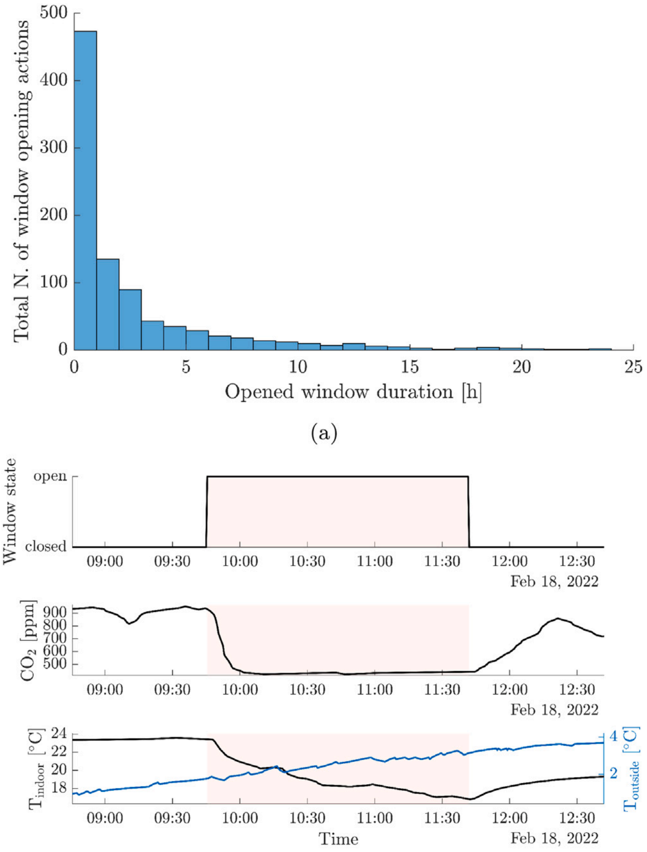
[4] The survey questionnaire is available at: github.com/MahsaFarjadnia/kth-lil-occupant-survey.



(a)

(b)

Fig. 8. (a) Distribution of window opening durations across all apartments during four winter seasons, and (b) example of prolonged window-opening duration observed for an occupant living in the Testbed KTH.

set of independent explanatory variables[5]: T_{indoor}, $T_{outside}$, DHI, RH, $\log(CO_2)$,[6] and day segments. To ensure that multicollinearity does not impact the performance and interpretability of the window operation model, Pearson's correlation coefficients among the environmental variables were assessed. Notably, the correlation between $T_{outside}$ and RH was found to be high, leading to the exclusion of RH from the analysis. The correlation values for other parameters confirmed the absence of significant multicollinearity in the training dataset. Fig. 10 provides an example of a correlation matrix, illustrating the relationships between indoor and outside environmental drivers and window status for one apartment during one of the considered winter seasons. The probability of a window-opening or window-closing event is modeled using the logit function as follows:

$$\ln\left(\frac{p}{1-p}\right) = \alpha + \beta_0 x_0 + \beta_1 x_1 + \cdots + \beta_n x_n, \tag{1}$$

where n represents the number of explanatory variables, denoted as x_i for $i = 0, \ldots, n$, α is the intercept corresponding to the day segments (DSs), and β_i denotes the coefficient associated with the explanatory variable x_i [45, Chapter 2.2]; [46]. For the analysis, we adopted a procedure similar to that presented in [24], with the addition of an explicit test step (Fig. 7). The following provides a summary of the model development procedure, which was applied separately to window-opening and window-closing data. The dataset was partitioned into training (80%) and test (20%) subsets. The training data underwent a 10-fold cross-validation process in which explanatory variables were selected using forward and backward stepwise regression based on the Akaike Information Criterion (AIC), reducing the risk of overfitting and underfitting. The final logistic regression model was then fitted using the selected variables and evaluated on the test dataset. The analysis and modeling were performed separately for window-opening and window-closing state changes. Accordingly, the dataset was partitioned based on the observed window state: the window-opening model was trained using only samples in which the window was *closed*, while the window-closing model was trained using only samples in which the window was *open*. Model performance was assessed using the area under the receiver operating characteristic curve (AUC-ROC), where an AUC of 1 indicates perfect classification. Note that the logistic regression model Eq. (1) predicts the probability of a window-opening or window-closing action. At each update step, this probability is converted into an action (0 = no action, 1 = action) using a model-specific threshold selected from the ROC curve on the evaluation dataset. The optimal threshold is determined in MATLAB using the `perfcurve` function and therefore differs across window-opening and window-closing models.

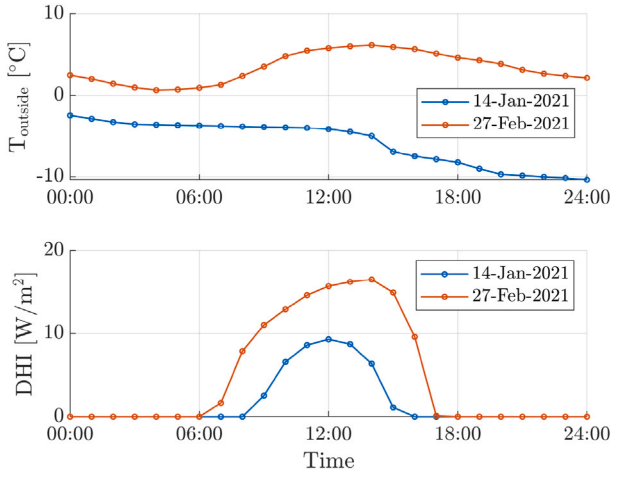
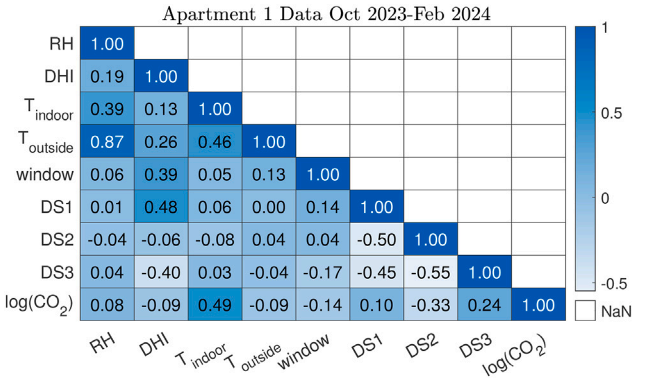


Fig. 9. Representative days selected for simulation: Typical day (27-Feb-2021) and colder-than-average day (14-Jan-2021). While only $T_{outside}$ and DHI are plotted, all other parameters are correctly configured in IDA ICE (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).



	RH	DHI	T_{indoor}	$T_{outside}$	window	DS1	DS2	DS3	$\log(CO_2)$
RH	1.00								
DHI	0.19	1.00							
T_{indoor}	0.39	0.13	1.00						
$T_{outside}$	0.87	0.26	0.46	1.00					
window	0.06	0.39	0.05	0.13	1.00				
DS1	0.01	0.48	0.06	0.00	0.14	1.00			
DS2	-0.04	-0.06	-0.08	0.04	0.04	-0.50	1.00		
DS3	0.04	-0.40	0.03	-0.04	-0.17	-0.45	-0.55	1.00	
$\log(CO_2)$	0.08	-0.09	0.49	-0.09	-0.14	0.10	-0.33	0.24	1.00

Fig. 10. Correlation matrix of various environmental variables and window status for apartment 1 from October 2023 to February 2024.

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[5] In this study, the terms "drivers" and "explanatory variables" are used interchangeably.

[6] $\log(CO_2)$ was used to achieve a better distribution for logistic regression analysis.

These models were then integrated into a simulation environment (Section 2.3) to assess the impact of window-operation behavior on energy consumption, as discussed in subsequent sections.

4.2. Representative days of winter climate in Stockholm

The outside climate conditions, including temperature and diffuse solar irradiance, are determined using a representative weather day approach, which provides a structured way to evaluate building energy performance under realistic winter conditions. Unlike the traditional design day method [47], which focuses on extreme heating and cooling loads, this approach considers statistically representative winter conditions, thus offering insights into occupant behavior and energy performance under more typical scenarios. This study defines two representative weather days based on winter data collected from October 2020 to February 2021, for which a calibrated IDA ICE model is available and corresponds to the layout presented in Fig. 1(e).

In particular, the representative days correspond to the median and the 10th percentile of the average daily outside temperature, representing typical winter conditions and a colder-than-average scenario (Fig. 9).

4.3. Measure of energy impact

To evaluate the energy impact of occupants' behavior, we focus on the energy consumption of the AHU system due to space heating, as directly obtained in IDA ICE. This total AHU energy use is denoted by $\mathrm{Q_{AHU}}$, and it is quantified by integrating the heating power, given by the following equation [48], over time:

$$\dot{\mathrm{Q}}_{\mathrm{AHU}} = \dot{\mathrm{m}}_{\mathrm{AHU}} \mathrm{C_{pa}} \Delta \mathrm{T_{AHU}}. \tag{2}$$

In (2), $\dot{\mathrm{Q}}_{\mathrm{AHU}}$ represents the space heating power delivered to the building by the ventilation system, $\dot{\mathrm{m}}_{\mathrm{AHU}}$ is the ventilation mass flow rate, $\mathrm{C_{pa}}$ denotes the air specific heat capacity, and $\Delta\mathrm{T_{AHU}}$ is the difference between the supplied air temperature ($\mathrm{T_{sa}}$) and the indoor temperature ($\mathrm{T_{indoor}}$).

The AHU energy consumption $\mathrm{Q_{AHU}}$ represents the aggregated value for the entire building (four apartments) rather than per apartment. To quantify the individual energy impact of occupant behaviors, we introduce the notion of *normalized energy increase (NEI)* per apartment. This metric is defined relative to a baseline scenario, where all occupants never open the windows. The NEI is defined as follows:

$$\mathrm{NEI} = \frac{\left(\mathrm{Q_{AHU}}/4 + (\mathrm{Q_{AHU}} - \mathrm{Q_{AHU_0}})\right)}{\mathrm{Q_{AHU_0}}/4},$$

where $\mathrm{Q_{AHU}}$ represents the total AHU energy consumption under occupant-driven window-opening and window-closing behaviors, and $\mathrm{Q_{AHU_0}}$ denotes the baseline AHU energy consumption when no window-opening actions occur throughout the simulation period. Note that the baseline scenario is used as an ideal energy-efficient *benchmark* rather than a representation of typical window-opening behavior in Swedish households. With all other model settings held constant, NEI quantifies the normalized increase in heating energy consumption due to window operation for the apartment with an integrated occupant behavior model.

5. Simulation results and discussion

This section presents the logistic regression models developed according to the methodology described in Section 4.1, using the experimental data introduced in Section 3. Detailed modeling results are provided in Section 5.1. The key contributions of this work are highlighted in Section 5.2, where simulation results from IDA ICE quantify the impact of occupant behavior on space-heating energy consumption. Finally, Section 5.3 discusses the challenges and potential future research directions.

Table 3
Median and interquartile range (Q1–Q3) for selected window-opening and window-closing models.

Metric	Opening windows Median (Q1–Q3)	Closing windows Median (Q1–Q3)
AUC-ROC	0.79 (0.72–0.83)	0.70 (0.69–0.73)
AUC-PR	0.71 (0.61–0.75)	0.65 (0.58–0.68)
Accuracy	0.79 (0.65–0.86)	0.67 (0.62–0.76)

Table 4
Estimated intercepts and coefficients for the window-opening and window-closing models of apartment 2, based on data collected from October 2021 to February 2022. The AUC-ROC values for window-opening and window-closing models are 0.74 and 0.81, respectively.

Drivers	Opening action			Closing action		
	Coeff.	Conf. interval		Coeff.	Conf. interval	
		2.5%	97.5%		2.5%	97.5%
α_{DS1}	0.22	0.20	0.23	0.94	0.89	0.98
α_{DS2}	−0.37	−0.39	−0.36	0.84	0.80	0.87
α_{DS3}	−2.76	−2.79	−2.73	0.23	0.17	0.29
$\beta_{\mathrm{T_{indoor}}}$	0.28	0.27	0.30	0.22	0.20	0.24
$\beta_{\log(\mathrm{CO_2})}$	0.57	0.56	0.58	0.09	0.05	0.14
$\beta_{\mathrm{T_{outside}}}$	0.42	0.41	0.43	−1.05	−1.07	−1.03
β_{DHI}	0.44	0.43	0.45	−0.01	−0.01	0.02

5.1. Performance of occupant behavior models

A total of 32 logistic regression models were developed to predict occupant-driven window operations: 16 models for window-opening actions and 16 for window-closing actions, following the methodology outlined in Section 4.1. These models were trained using winter-season data collected over a four-year period (2020–2024), during which different occupants resided in the apartments each year. To determine which models were used in the co-simulation, we applied a model selection procedure based on AUC-ROC and accuracy. Models with an AUC-ROC of at least 0.6 were selected. In addition, models with unreliable accuracy (less than 0.55) were considered less robust and excluded. Based on these criteria, 12 models (6 for window opening and 6 for window closing) were selected to represent occupant behavior in the Testbed KTH digital model. Table 3 summarizes the quantitative performance of the selected models, categorized by AUC-ROC, area under the precision–recall curve (AUC-PR), and accuracy quartiles. Table 4 provides examples of high-performing logistic regression models obtained using the described methodology.[7]

5.2. Energy consumption analysis

In this section, using the 12 window operation models derived in the previous section, 12 virtual occupant behavior (OB) profiles are defined for the Testbed KTH. Each occupant exhibits distinct sensitivity to indoor and outdoor environmental conditions, resulting in unique window operation behaviors. These profiles are integrated into the digital model of the building in IDA ICE to evaluate the impact of window-opening and window-closing actions on AHU energy consumption. To ensure a comprehensive evaluation, we assume in the IDA ICE model that occupants are continuously present throughout the 24-hour simulation, which is conducted for two representative winter days: one typical winter day and one colder-than-average winter day. Based on survey results, two window-opening extents are considered: 10% (partially open) and 100% (fully open). Each occupant behavior profile is applied separately to the

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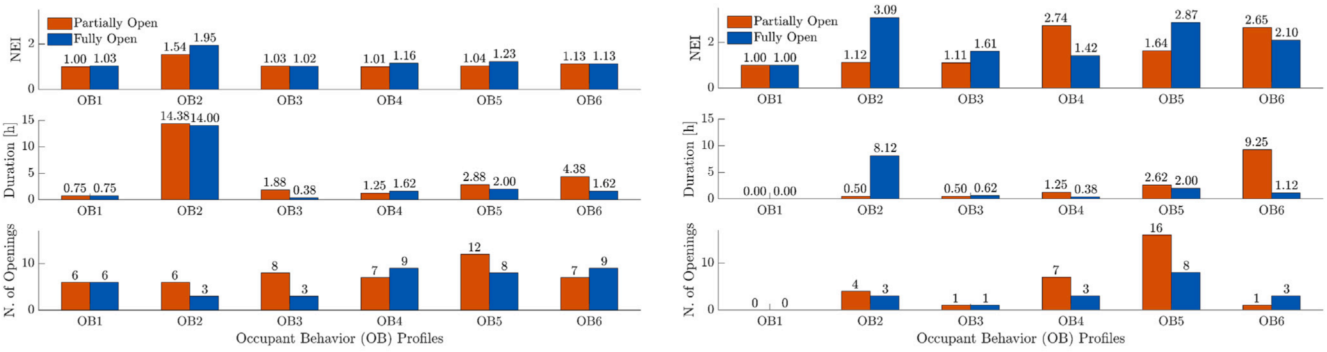
[7] The complete set of logistic regression models, along with detailed coefficient estimates, is available at the GitHub repository: github.com/MahsaFarjadnia/window-operation-models-kth.



(a) (b)

Fig. 11. Normalized AHU energy consumption increase per apartment considering different occupants' behavior (OB) profiles, total window-opening duration, and the number of window-opening actions on two representative winter days: (a) a typical winter day and (b) a colder-than-average winter day. Two window-opening extents are indicated: red for partially open (10%) and blue for fully open (100%) (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

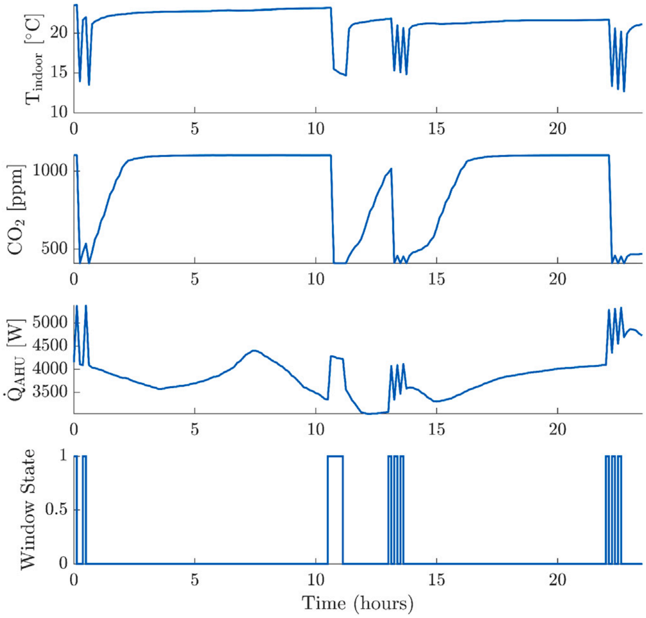


Fig. 12. Example of an impact of window operation on indoor temperature (T_{indoor}), CO_2 concentration, and AHU power consumption ($\dot{Q}_{\text{AHU}}$) over a 24-hour simulation period.

same apartment model in IDA ICE, while the windows in the remaining three apartments are kept closed throughout the simulation.

The top subfigure in Fig. 11 illustrates the NEI per apartment due to window opening across different OB profiles, alongside the total daily window opening duration and the number of window opening actions over a 24-hour simulation. The results indicate that NEI is generally higher on the colder-than-average day than on the typical winter day. Furthermore, the window-opening event durations observed in the co-simulation are consistent with the monitored window-state data (Section 3). In particular, occupant profiles associated with apartment–year combinations that exhibit long opening events in the measurements (e.g., OB2) also produce long total daily opening durations in co-simulation. For a small number of profiles (e.g., OB5), the co-simulation predicts a higher number of window-opening actions per day than observed in the monitoring data (see footnote 3). However, these cases do not correspond to the highest NEI values and therefore do not affect the overall interpretation discussed in Section 5.3. A comparison of the two top subfigures further suggests that there is no clear direct relationship between NEI and total window opening duration alone. However, additional factors, such as wind speed and wind direction at the time of window openings, can lead to variations in energy impact beyond what is explained by total window opening duration alone.

Fig. 12 illustrates an example of the time-series variations in T_{indoor}, CO_2 concentration, $\dot{Q}_{\text{AHU}}$, and window state over a 24-hour period. The results indicate that window-opening events lead to a sharp decline in CO_2 concentration and a rapid drop in T_{indoor}, triggering an increase in $\dot{Q}_{\text{AHU}}$ as the system compensates for heat losses. These findings highlight the significant influence of window operation patterns on both ventilation effectiveness and heating energy consumption.

5.3. *Discussion*

The results presented in Section 5.2 highlight the significant impact of occupant-driven window operation on heating energy use in residential buildings. This section discusses the implications of these findings in relation to energy performance, ventilation strategies, and occupant behavior modeling. It also outlines the limitations of the current approach and potential directions for future research.

One of the key goals of the co-simulation framework is to provide a controlled comparison of different occupant behavior profiles under identical boundary conditions. With all conditions held constant, any differences in heating energy use reflect only differences in occupant behavior profiles and are benchmarked against a baseline case with no window opening. While using measured window-state time series instead of logistic regression models can quantify the impact of occupant behavior profiles on energy consumption in the digital model, it imposes an open-loop schedule that is specific to the monitoring period. In contrast, data-driven models respond to simulated indoor and outdoor conditions and can be run in closed-loop, allowing flexible scenario comparisons and supporting future investigations of human-in-the-loop control strategies.

Using this framework, NEI reaches a peak value of 3.09 times the baseline scenario (Fig. 11), representing a substantial energy loss. On average, NEI is approximately 1.53 times the baseline, highlighting the considerable impact of window-opening behavior on energy performance. These findings highlight the need for advanced, individualized ventilation strategies, such as real-time, adaptive, data-driven HVAC control systems, that account for diverse comfort preferences [49–51]. Additionally, occupant awareness programs are essential to reduce unnecessary heat losses while maintaining adequate indoor air quality [52].

It is also important to note limitations and point out directions for future work. First, the assumption of constant occupancy presence may not represent real-world absence/presence patterns across households and may affect absolute energy values through internal gains. However, it preserves time-of-day effects in occupant behavior. Future work will incorporate measured or inferred occupancy schedules and conduct sensitivity analyses to quantify the influence of presence patterns on the predicted energy impacts. Second, all behavior profiles are integrated into a single calibrated apartment. This choice was made to isolate behavioral differences and allow a controlled comparison across profiles, independent of layout effects. Moreover, constraints in data collection, such as low records of occupant activity, also caused some models to perform below the study's acceptance threshold. These models were therefore excluded from the final analysis. Improving data quality and availability would significantly enhance model accuracy and generalizability. Lastly, while logistic regression has shown reliability in previous studies, it provides a simplified representation, and it may not fully capture the more complex behavioral patterns identified in recent survey data. Ongoing research is investigating more advanced, data-driven modeling techniques to address these complexities, although the integration of such methods lies beyond the scope of the present work.

This study considered thermal and indoor air quality among the four principal forms of indoor environmental quality [6]. Visual and aural comfort were not analyzed, as the KTH Testbed is located in a quiet area with minimal external noise, and most of the time, curtains were drawn due to the large windows on the ground floor.

Following Annex 79 [6], this study explicitly accounts for contextual variability by incorporating data from multiple apartment layouts and different occupants living there across different time periods. This diversification of behavioral profiles enhances the robustness of the results and demonstrates that the findings can be applied to similar buildings and climates using commonly available data. Finally, this study leverages data from a real building and its calibrated digital model, accurately representing its physical and operational characteristics. Using this hybrid approach, combining measured building data with a calibrated digital model, the study demonstrates a scalable proof of concept for assessing the impact of occupant behavior on building energy performance, and it further paves the way for real-time user feedback strategies and occupant-centric building control design.

6. Conclusion

This study investigates the impact of occupant-specific window-operation behavior on energy performance of residential buildings, using data from Testbed KTH and closed-loop co-simulation (IDA ICE–MATLAB) with a calibrated building model. By leveraging sensor data collected over four winter seasons, logistic regression models were developed to capture individual occupants' window-opening and closing behaviors. These models were integrated into a digital model of Testbed KTH and evaluated under identical boundary conditions against a consistent closed-window reference case. The findings demonstrate that occupant behavior plays a critical role in space-heating energy consumption. Window-opening actions can lead to a significant increase in normalized space-heating energy use, with some cases showing up to three times higher energy use compared to a scenario with no window interactions. Moreover, the results highlight the variability in window operation patterns among different occupants, emphasizing the need for individualized modeling approaches rather than assuming fixed or uniform schedules. These insights underscore the importance of closed-loop integration of occupant behavior models within building performance simulations and control designs.

CRediT authorship contribution statement

Mahsa Farjadnia: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis. **Angela Fontan:** Writing – review & editing, Visualization, Methodology, Writing – original draft, Validation. **Karl Henrik Johansson:** Writing – review & editing, Supervision, Funding acquisition. **Marco Molinari:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization.

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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Data availability

The data that has been used is confidential.

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