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Investigation on window opening and closing behavior in schools through measurements and surveys: A case study in Budapest

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Title

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Abstract

In this study, a multidisciplinary approach has been adopted to observe and investigate window opening and closing behavior in two classrooms of a Hungarian school. Surveys and measurements have been used to identify environmental, contextual or habitual drivers of window use. For this purpose, 8-months long time-series datasets and qualitative teacher interviews were the tools used to investigate behavior. The two classrooms have identical boundary conditions; however, drivers for window adjustments were observed to be different. In one case, window use is primarily triggered by habits and time-dependent actions, whereas, in the second one, environmental parameters are the key drivers. In the latter case, stochastic behavioral models have been developed aiming at a future implementation in energy simulations. In the literature, few studies focused on analyzing these phenomena, resorting to interdisciplinary methods to reach a comprehensive understanding of occupants' behavior. Moreover, assessing behavior can lead to an optimization of the indoor environment, which is of primary importance in school buildings both in terms of energy use and pupils' health.

Keywords

Sustainable building; energy efficiency; occupant behavior; window use; behavioral modeling

1. Introduction

The European Union’s main building energy performance-related legislative instruments are driving improvements in the energy performance of the building stock in the European Union [1–3]. By 2020, all new buildings must be nearly-zero energy buildings. Building energy regulations focus on increasing the performance of building structures and energy supply systems. This way, overall energy use associated with building characteristics is decreasing. However, without considering the human dimension, technologies alone do not necessarily guarantee high performance in buildings [4–6].

In fact, human behavior plays an essential role in the buildings’ energy-related behavior [7]. When an occupant turns on the heating, opens the window or switches on the light, the energy balance of the building changes and affects the overall energy consumptions. In particular, in low- and passive energy buildings, the role of the occupants is more important than ever.

Currently, there is a significant discrepancy between simulated results and actual energy consumption [8]. The core issues mainly stem from a lack of appropriate representation of occupants’ thermal preferences and their energy-related behavior [9,10]. Specifically, occupant behavior is currently represented via oversimplified and predefined deterministic schedules or fixed rules in simulation, which result in deterministic results that do not reflect the stochastic, dynamics, and diversity of occupant nature.

1.1 Approaches to Investigate Occupant Behavior in Buildings

Building energy professionals make the assumption that occupant behavior primarily refers to users’ comfort preferences, presence and movement, and adaptive interactions with building systems that have significant impacts on the performance of buildings (e.g., thermal, visual, and acoustic comfort provisions; indoor air quality; energy use) [4,11,12]. Such interactions include adjusting thermostat settings, opening or closing windows, dimming or turning on/off lights, pulling up or down window shades and blinds and switching on or off plug loads.

For example, occupants can open windows due to various reasons: (1) feeling hot (thermal comfort driven), (2) feeling stuffy (indoor air quality driven), and (3) because of habit, arriving in a space (event-driven). Such determinants of window opening actions have been confirmed through multiple large-scale surveys and field studies [13,14]. Probabilistic models, developed from these studies, have in turn been adopted by several energy simulation programs to improve the representation of realistic adaptive occupant activities [15].

The approach of researchers in social science focuses on the psychological and social aspects of the occupants' decision-making process. Influencing factors and attitudes are determined that may affect the undertaking of a certain action. The effects of the actions are investigated in a wider, human dimension. Rather than focusing on the impact on energy balance or thermal comfort in a room, researchers investigate group dynamics, social norms and environmental psychology aspects [16].

The main difference between these two approaches lays in the diversity of aspects and phase of energy-related human behavior under the microscope.

The two approaches, starting from opposite point of views, are complementary in studying the behavioral field. Thus, a multidisciplinary approach would be suitable for an extensive insight into human behavior.

1.2 State-of-the-art of Window Use Drivers in Schools

One of the key behavior types investigated in this field of research is the use of windows since it concerns both thermal comfort and air quality as well as energy consumptions. Window opening actions provide an air exchange between rooms and the outdoor environment thus affecting the indoor thermal parameters and pollutant levels. This phenomenon is widely investigated in recent literature [17] [18] where high indoor CO_2 levels and other pollutants might have a long-term impact on human health.

Many investigations have been performed in offices [13,14] and residential buildings [15], while studies concerning the window use in schools are much less frequent. School classrooms present great differences of boundary and contextual conditions (e.g. number and age of users, freedom of action, group rules) compared to offices and residential settings but many outcomes were found to be very similar [19].

In particular, thermal comfort is the crucial factor for windows' interaction. Indoor and outdoor temperatures are the main stimuli that trigger both openings and closings [20,21]. In fact, students are more sensitive to thermal than to IAQ discomfort [22]. As a consequence, pupils usually suffer very high CO_2 levels which compromise their health and well-being in case of window-ventilated classrooms [23,24].

In schools, the daily timetable and the routine are extremely influencing on deciding the windows status. Arrivals and breaks are the preferred moments to adjust windows [21,25]. In fact, often teachers dictate the management of the classroom, while during breaks students can freely interact with the windows [26]. Moreover, during lessons, students are focused on the tasks and so, their sensitiveness to environmental discomfort decreases.

Even if educational conditions, rules and, habits can greatly vary between different schools and countries, researchers agree that thermal comfort and IAQ are usually extremely poor in classrooms, especially in naturally ventilated ones [22,26].

1.3 Current Study and Research Theorems

This study was conducted as part of the NewTREND project (Horizon 2020) [27]. One of the selected demonstration sites is an elementary school building, located in Budapest (Hungary). Two similar classrooms have been selected to observe occupants' behavior on windows and to adopt a multidisciplinary approach to investigate both objective and contextual driving factors.

Moreover, the analysis of previous studies and empirical observations lead to some preliminary hypotheses, listed below and discussed according to the obtained results.

I. Window opening/closing behavior is correlated to environmental parameters (i.e. indoor temperature, outdoor temperature, CO_2 concentration).

II. Similar behavior can be observed in both classrooms since the boundary conditions are analogous.

III. Social norms and habits influence the behavior patterns.

2. Methods

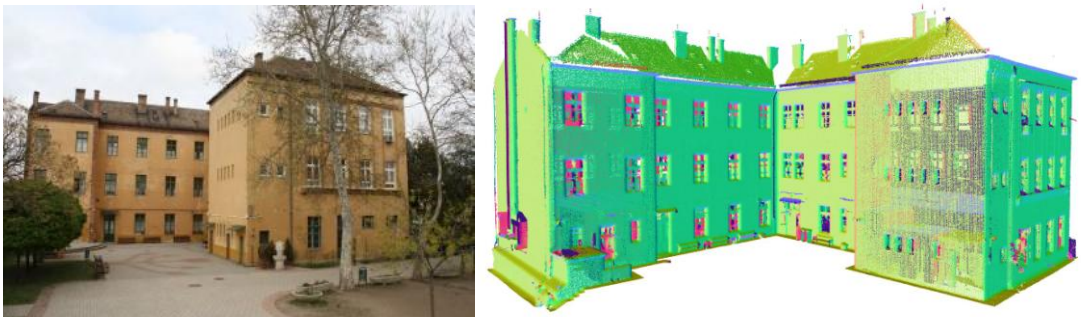
The research has been carried out following the subsequent steps:

1. Screening: selection of two classrooms to investigate the thermal environment and the users' behaviors through measurements and surveys;
2. Data collection: development and application of the required sensor network for environmental monitoring (indoor and outdoor thermal conditions and IAQ);
3. Data cleaning and processing: carried out to ensure good quality of data, this step was followed by the adjustment of data point collection frequencies with linear interpolation;
4. Preliminary analysis: correlations between environmental parameters and students' actions have been statistically evaluated to assess whether they are connected;
5. Behavioral models development: if the correlations were promising, a regression analysis has been performed to obtain models to predict users-windows interaction;
6. Time-related analysis: opening and closing behaviors have been studied in relation to the time of the day to check if habits and timetable influenced windows' adjustments;
7. Teachers' opinion: personal interviews with teachers have been carried out to investigate typical classroom's behaviors, rules and group norms;
8. Interpretation: the results related to the two classrooms have been compared each other and to previous studies concerning schools in different climates.

2.1 Building's Physical and Contextual Characteristics

The elementary school building serving as the experimental setting for this project was built in 1903 and is located in district 18 of Budapest (latitude: 47.44, longitude: 19.18, altitude: 133 m). See Figure 1 for 3D geometry.

As a first step, onsite walk-throughs were conducted to map the overall condition and use of the building. Interviews with local personnel and other stakeholders helped in obtaining the original architectural plans and in identifying the organizational structure, HVAC and electrical systems of the building. Geometrical parameters and dimensions were measured by laser scanning technology.



(a) (b)

Figure 1 Picture (a) and laser-scanned image (b) of the school building.

2.2 Environmental Monitoring

The complaints of teachers bring to the identification of two classrooms characterized by thermal comfort issues during winter seasons. The classrooms are located on top of each other with the same dimensions and the same orientation. Table 1 contains their main characteristics.

Table 1 Main characteristics of the two classrooms investigated

Classroom	**1**	**2**
Floor	2nd	1st
Net floor area (m^2)	28.6	28.6
Room height (m)	3.8	3.8
Room volume (m^3)	109.6	109.6
Orientation	South-East	South-East
Nr. of windows	2	2
Type of windows	Historic double skin box-type	Historic double skin box-type
Maximum nr. of pupils	20	20
Nr. of teachers using the room	2	1

To investigate behavioral patterns and the causes of thermal discomfort, indoor and outdoor conditions and window opening actions have been monitored for 8 months (Figure 2). The data refer to the period from the 15/02/2017 to 20/09/2017, with a summer break in the middle (15/06/2017-31/08/2017).

Figure 2 Indoor monitoring device locations in classrooms

Table 2 reports the characteristics of the installed sensors. Indoor dry-bulb temperature and window opening sensors were placed in both classrooms whereas indoor CO_2 sensor could be installed only in Classroom 2. The selected CO_2 sensor has a measurement range of 0-2000ppm, which is the range where most of the triggering thresholds are located. In any case, given the fact that concentrations higher than 2000ppm could occur, a sensor with a larger range should be used for an in-depth analysis. An outdoor weather station logged the outdoor dry-bulb temperature.

Table 2 IEQ monitoring sensor specifications

Measured parameter	**Applied sensor**	**Nr. of sensors**	**Range**	**Accuracy**	**Acquisition rate**
Indoor dry-bulb air temperature	QAA 910, NTC 10 kOhm resistor	2	0…50 °C	±2%	30 s
Outdoor dry-bulb temperature	QAC 910, NTC 1 kOhm	1	-50...50 °C	±2%	15 min
Indoor CO_2 level	QPA 2000, NDIR Symaro	1	0…2000 ppm	≤± (50 ppm + 2 %)	30 s
Window opening	Gamma wave	4 with 2 signals	0 (closed), 1 (open)	N/A	30 s

Two time-series datasets were compiled based on the data monitored in the two classrooms to investigate window opening and closing behaviors. The two dataset used for analyses and evaluations include the data all acquired during the monitoring. The objective investigations were supplemented with interviews with the teachers using the room. After an analysis of three different time-steps (5, 10, 15 mins) in terms of user behavior representativeness, both datasets were interpolated to 15 minutes time-step, which was found to be still a good representation of behavior, and also to provide shorter computational time Fragments of these datesets can be seen on the following Figures where window status can be seen in connection with indoor and outdoor temperature levels. (Classroom 1 – Figure 3, Classroom 2 – Figure 4.)

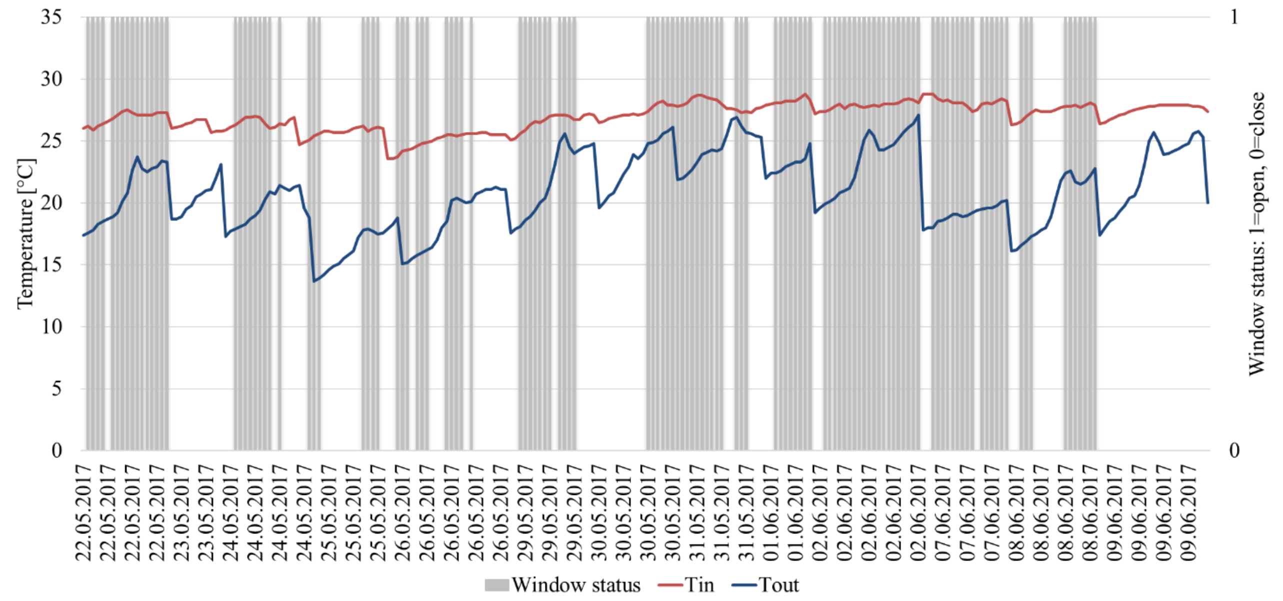


Figure 3 Classroom 1 dataset fragment: 22/05/2017-09/06/2017

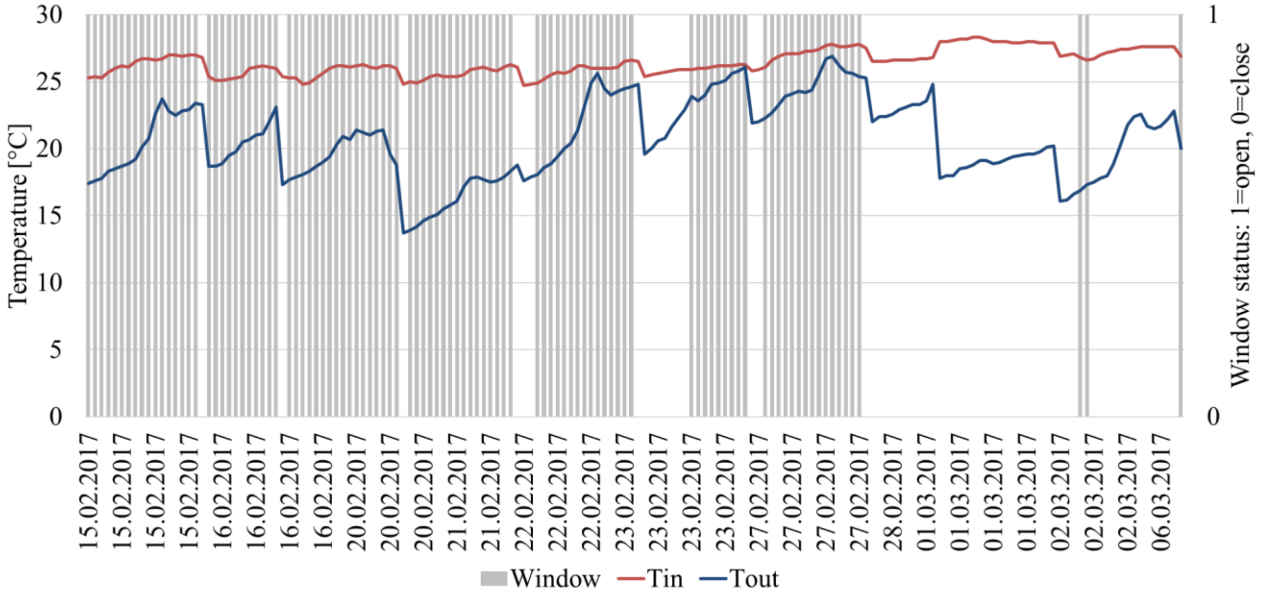


Figure 4 Classroom 2 datasets fragment: 22/05/2017-09/06/2017

2.3 Teacher Interviews

Qualitative individual interviews with teachers using the classrooms have been conducted in November, after the data collection campaign. Classroom 1 has been used by two teachers, one of them was interviewed. Classroom 2 has been used by one teacher who could not be interviewed. Her attitude, personality and daily routine have been collected from the headmaster.

Both interviews have been conducted by telephone in a previously negotiated time to allow interviewees the freedom to choose the appropriate timing. This way the interview could be conducted in a comfortable environment, where respondents appeared to speak freely. To drive the interview flow, an interview guide document has been prepared to make sure the comprehensiveness and also that all main aspects are touched upon during the conversations.

Although the interview sample size does not allow for statistical generalization, it gives a very precise picture with an appropriate resolution on the behavior, daily schedule and attitude of different teachers.

2.4 Statistical Data Analysis and Modeling Method

The preliminary analytical phase concerned the statistical study of correlations between occupants' actions and environmental variables. The recorded parameters and the window opening and closing behaviors have been examined through a regression analysis.

The outputs of this analysis are the p-value and three goodness-of-fit (GOF) estimators which identifies the statistical significance of the investigated variable and the strength of each correlation, respectively. Specifically, three different indexes have been calculated: the Area Under the Receiver Operating Characteristic (AUROC) curve, the McFadden's R^2 and, the Nagelkerke's R^2 [28]. The higher these values are, the more the variables are linked. In detail, the AUROC curve graphically represents the true positive and the false positive rates at various threshold settings obtained from the predictions of a binary classifier system (e.g. a logistic regression model) on real data. The index ranges between 0.5 (no correlation at all) and 1 (perfect correlation) but values around 0.7 are considered enough satisfying. The two pseudo-R^2 have a similar meaning to the R^2 used for linear regressions. Although the formers are generally lower than the latter, the pseudo-R^2 are preferred when the dependent variable is dichotomous (in the present case, 0 refers to closed and 1 to open windows).

The correlations that showed satisfying estimators have been selected for the development of behavioral models for window opening and closing. Logistic regression is one of the most adopted methods to develop behavioral models, especially for dichotomous outcomes (e.g. 0=window closed 1=window open). Many studies [29,30] employed such approach for estimating the probability of an action in response to one or more predictor variables and in different contexts [31,32]. Logistic regressions usually provide good approximations of occupants' behaviors because the S-shape of the functions realistically reflects the human-environmental mutual influence. However, the main disadvantage of this method lies in the lack in representing the absolute threshold above or under which the human-building interaction does not occur.

Targeting at overcoming such limitation, Wang et al. [33] proposed a modeling method which combines both regression methods and absolute thresholds. The approach has been adopted in this paper to model window adjustments. The suggested mathematical form is a discrete three-parameter Weibull cumulative function. Equations 1 and 2 show the increasing and decreasing forms, respectively. The former has been used to model window opening and the latter for closing behaviors.

$$F(x) = \begin{cases} 1 - e^{\left(\frac{x-u}{l}\right)^{k}\frac{\Delta\tau}{\tau c}} & if\ x > u \\ 0 & if\ x \leq u \end{cases} \tag{1}$$

$$F(x) = \begin{cases} 1 - e^{\left(\frac{u-x}{l}\right)^{k}\frac{\Delta\tau}{\tau c}} & if\ x < u \\ 0 & if\ x \geq u \end{cases} \tag{2}$$

In the equations, the variable x is the environmental trigger, the parameters u, l, and k are three constant coefficients that need to be experimentally derived; $\Delta\tau$ is a discrete time step in the measurement (in the case, 15 minutes); and τ_c is a pre-determined time constant (in the case, 60 minutes).

The models have been developed considering only the occupied periods since students' presence is a necessary condition for windows interaction. The coefficients of each algorithm have been derived using a regression analysis. Statistical estimators to clarify how much the regression models fit the observational data have been provided too. Expressly, the reported GOF estimators are: the sum of squared errors (SSE), the R^2, the adjusted R^2 and, the root mean squared error (RMSE). Better fits are identified by higher values of these parameters.

This approach has been previously applied to predict the air-conditioning use in residential buildings [34] and the light switching behavior in offices [33]. The latter has been coupled with an Agent Based Model (ABM) [35] to perform an individual representation of occupants' behaviors. In this paper, the described modeling approach has been adopted, for the first time, to predict windows status in school classrooms.

3. Results

This section presents the main outcomes of the experimental research. Sub-sections 3.1 and 3.2 report the results related to objective and subjective assessments of Classroom 1. Then, sub-sections 3.3 and 3.4, following the same structure, describe the findings concerning Classroom 2.

3.1 Classroom 1, Modeling Results

This section illustrates the behavioral models obtained with the data all recorded in Classroom 1.

A preliminary analysis has been performed to understand whether users' actions on windows were driven by environmental variables. Table 3 presents the results of these analyses, illustrating the number of observations, the p-values and three GOF estimators for each couple of action and triggering factor. The p-values lower than 0.001 and the values of the estimators suggest that students' behaviors could be related to the investigated environmental parameters.

Table 3. Goodness-of-fit estimators for each correlation of Classroom 1

Action - Trigger	**Num. observations**	**p-value**	**AUROC**	**McFadden's R^2**	**Naglekerke's R^2**
Window opening – indoor temperature	985	0.000	0.62	0.02	0.03
Window opening – outdoor temperature	985	0.000	0.61	0.02	0.03
Window closing – indoor temperature	517	0.000	0.68	0.06	0.09

Window closing – outdoor temperature	517		0.000	0.62	0.03		0.04

The subsequent evaluation concerns the development of the behavioral models. In particular, Table 4 reports the coefficients and the GOF estimators for the correlation models, while Figure 5 and Figure 6 display, for each model, the observational data, the regression model, and the prediction bounds (90%). In particular, the prediction bounds graphically indicate the uncertainty of the fit on the observations. The applied level of certainty indicates that there is a 90% chance that a new observation will occur within the bounds. The formula adopted to calculate the prediction bounds is reported in Equation 3:

$$P_o = \hat{y} \pm f\sqrt{s^2 + xSx'} \qquad (3)$$

Where, $\hat{y}$ is the new observation, x is the predictor value, s^2 is the mean squared error, f is the inverse of the F cumulative distribution function and S is the covariance matrix of the coefficient estimates.

The models present a good agreement with the observational data. The best correlation is the one relating window opening and indoor temperature (Adjusted R^2: 0.9), while the weakest is that linking window opening and outdoor temperature (Adjusted R^2: 0.26). The behavioral models estimating the opening probability follow an increasing trend, namely that when the temperatures levels increase the opening probability increases as well. Conversely, the models connected to the closing probability present an increase in the probability of interaction at the parameters decreasing.

Table 4. Coefficients and goodness-of-fit estimators for each model

Action-Trigger	**u**	**l**	**k**	**SSE**	**R^2**	**Adjusted R^2**	**RMSE**
Window opening – indoor temperature	20	5.72 (4.84–6.61)	1.15 (0.64–1.66)	0.005	0.913	0.9	0.027
Window opening – outdoor temperature	-0.3	16.46 (8.76–24.16)	0.9887 (-0.10–2.08)	0.127	0.309	0.26	0.1
Window closing – indoor temperature	30	3.77 (2.74– 4.8)	1.785 (0.87– 2.7)	0.02	0.89	0.87	0.05
Window closing – outdoor temperature	30	9.4 (3.62–15.53)	1.03 (0.21–1.85)	0.06	0.71	0.68	0.086

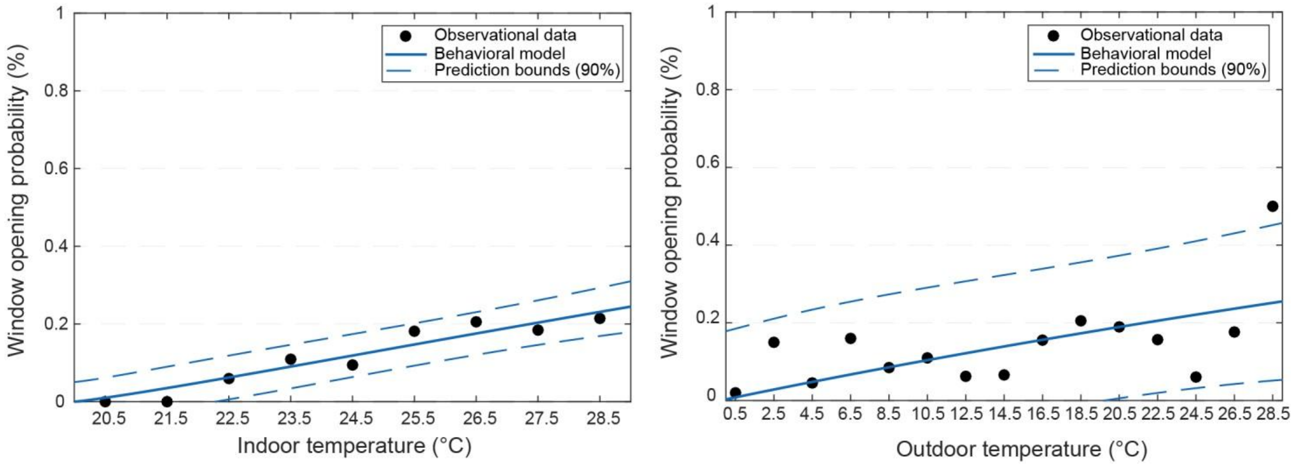


Figure 5 Window opening probability functions - classroom 1

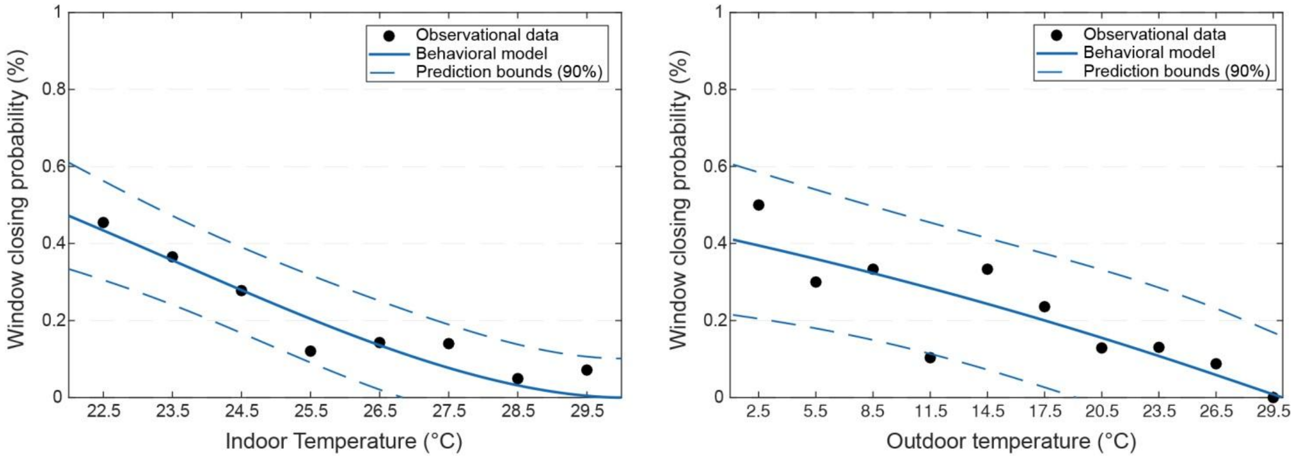


Figure 6 Window closing probability functions - classroom 1

Aiming at an exhaustive assessment of students' behaviors, the opening and closing actions have been studied in relation to time intervals of 15 minutes. The relative frequencies of openings and closings have been calculated on the data recorded during the whole survey. The values describe the ratio of the number of actions occurred to the number of occasions on which they might occur, during each time interval. **Error! Reference source not found.**7 illustrates the results of the analysis.

It can be noted that the peaks of interactions are focused in similar time spans (e.g. around 8:00 and 9:00) and, in particular during breaks. Window openings are more frequent during the first part of the morning while closing behaviors are concentrated at arrivals (i.e. around 8:00) and at departures (i.e. 12:30).

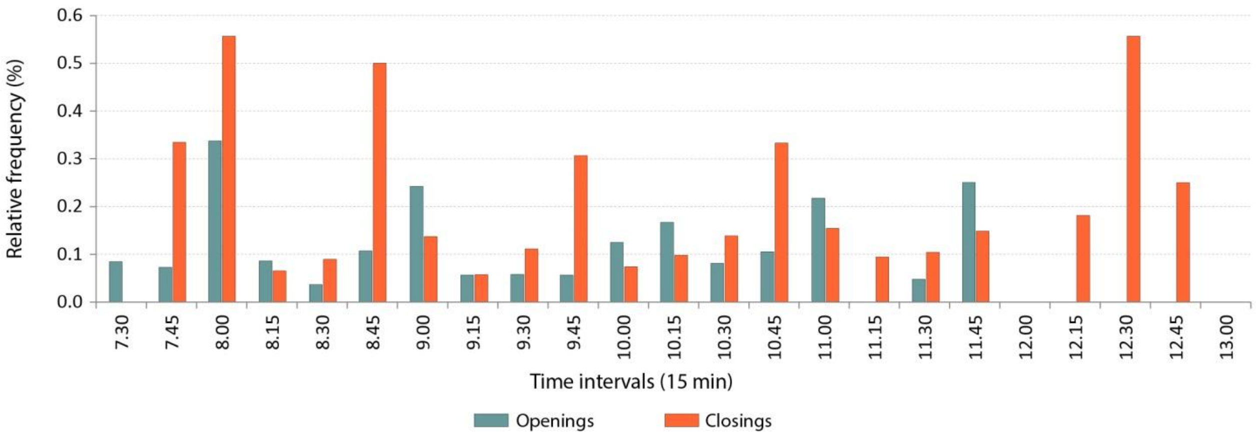


Figure 7. Opening and closings times - classroom 1

3.2 Classroom 1, Key Interview Findings

According to the interview results, it was found that teachers using this room stay in the classroom only for the classes. As they have classes in different classrooms during the day, they usually use the breaks for migrating to other classrooms. During the classes, they generally open the windows for fresh air when children complain of bad smell or stuffy air.

In this classroom, children are also allowed to open windows with teacher's supervision whenever needed during the classes. Therefore, window opening actions are carried out when needed and not restricted by social or contextual factors. Based on the interview answers, opening depends on the weather, if it's too cold, they don't open it.

3.3 Classroom 2, Modeling Results

This section reports the analyses performed with the entire dataset related to Classroom 2, starting from the assessment of correlations between users' behaviors and environmental parameters.

Table 5 reports the number of observations, the p-value and three different estimators for each correlation. Unlike the Classroom 1, the p-values are higher than 0.001 (except for window closing-indoor temperature correlation) and the goodness-of-fit all are extremely weak. It means that no statistical correlation lies between such parameters and, as a consequence, no behavioral model can be obtained.

Table 5. Goodness-of-fit estimators for each correlation of Classroom 2

Action-Trigger	Num. observations	p-value	AUROC	McFadden's R^2	Naglekerke's R^2
Window opening – CO_2 concentration	674	0.009	0.59	0.013	0.019
Window opening – indoor temperature	674	0.783	0.5	0	0
Window opening – outdoor temperature	674	0.706	0.5	0	0
Window closing – indoor temperature	882	0.000	0.62	0.025	0.033
Window closing – outdoor temperature	882	0.327	0.54	0.002	0.002

These outcomes suggest that the thermal environment and air quality requirements are not the main stimuli which have driven users in Classroom 2.

In accordance with the literature, the relationship between opening/closing actions and the time of the day has been investigated, dividing the teaching time into 5 minutes time steps. Figure 8 displays the relative frequencies for opening and closing events recorded during the whole monitoring period.

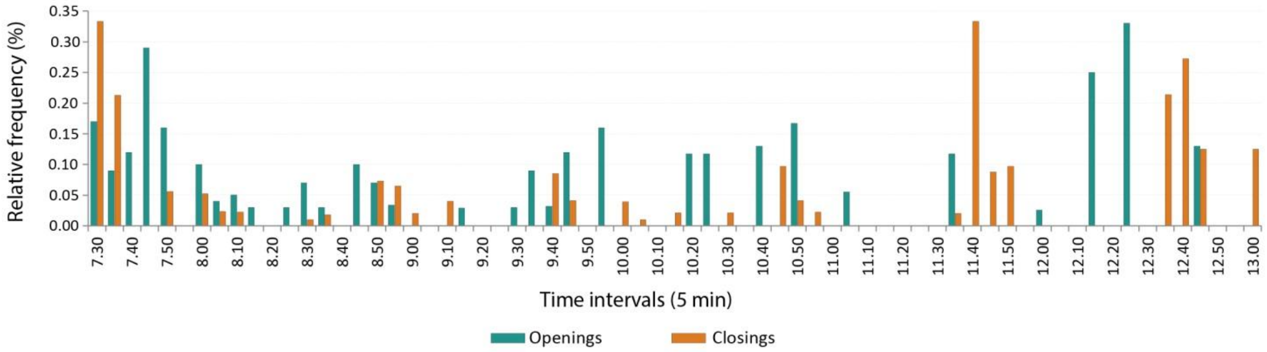


Figure 8 Opening and closing times - classroom 2

Similarly to Classroom 1, many of the peaks of interaction can be observed at the same intervals. The early morning (i.e. at arrival) and at the end of the lesson time (i.e. at departure) are the preferred moments to adjust window status, while interactions during the occupied periods are less frequent.

3.4 Classroom 2, Key Interview Findings

Based on the headmaster’s answers, it could be determined that the teacher stayed in the classroom 2 all day, including breaks. Her everyday routine started early (20 minutes before classes) by occupying the classroom for the whole day. Upon arrival and during the intervals between classes, she opened the windows for fresh air.

In this classroom, children were not allowed to open windows due to security reasons (not to fall out of the window). As the teacher let in fresh air in every break, window opening behavior was independent of the weather and indoor climate and this way of the potential complaints of children related to indoor air quality.

4. Discussion

4.1 Comparing the Behavioral Models Obtained to Literature

The behavioral models related to Classroom 1 confirm previous findings. Indoor and outdoor temperatures are the key parameters that trigger users’ actions on windows [21]. In particular, indoor temperature is the best predictor of both openings and closings behaviors. These results are in accordance with previous studies performed in similar building uses but in different climate zones [25].

The observed time-related behaviors are in accordance with results from the literature. Arrivals, departures and breaks are the preferred moments to intervene on windows [25]. Conversely, during the lessons, the presence of the teacher and the pupils’ attention to the lecture lead to a sensible decreasing in windows’ adjustments [26].

These findings provide a first aid in this direction; however, further research is needed to validate the obtained results for a wider sample and to analyze students’ actions in different seasons and climates.

4.2 Differences in Behavior in the Two Classrooms

The analyses performed in Classroom 2 highlight that no statistical correlation could be found between window use and environmental parameters. This was against the stochastic behavioral modeling literature [13, 30-33] but considerably in line with existing social-behavioral models [37–40], that state that the behavior of a person is highly dependent on both external and internal factors. By means of the interviews conducted with teachers using the classrooms, essential internal and social differences could be identified, that were found to be the reason between the different behavioral patterns observed in the two classrooms.

Classroom 1 was operated by two teachers constantly changing classrooms in breaks. As children are not allowed to open the windows according to national regulations, teachers opened the windows only during classes, based on the observations and complaints of children (i.e. thermal discomfort-driven).

Classroom 2 was occupied by only one teacher during all classes. According to our interviews, this teacher was not leaving the classroom during the day and she opened the windows in all of the breaks to “let enough fresh air in”, independently from the outdoor or indoor temperature levels. Children’ complaints were not considered during the classes.

Such behavioral differences between occupied spaces with similar physical settings are rarely described in the literature yet. Therefore, future studies and investigations on the effect of contextual and social behavioral aspects in case of energy-related occupant behavior studies are extremely needed.

4.3 Theorem Results

The research theorems expressed at the beginning of the project have been investigated and discussed.

I. Is window opening/closing behavior strongly correlated to measured environmental parameters? It is true in case of Classroom 1 as strong correlations have been found and stochastic data-driven behavioral models could be built. Whereas, it is false in case of Classroom 2.

II. Can similar behavior be observed in both classrooms? No, since window use greatly differs between the two spaces.

III. Do social norms and habits influence the behavioral patterns in case of the window opening and closing? Yes. Based on interview results, it could be proved that social norms and habits influence the behavioral patterns.

The results of this work suggest some building design-related considerations. In building performance simulation, occupant behavior can be represented with fixed profiles or, until recently, using stochastic behavioral functions. Even if, currently, the second approach tends to be preferred to represent the variability among the users, the differences recorded in this study suggest that, in some cases, a hybrid approach could be more appropriate.

School buildings are complex spaces both in terms of privacy issues (presence of minors) and building regulation. For this reason, it is of primary importance arranging an experimental set-up tuned on the specific building both to achieve reliable measurement and perform valuable surveys. In fact, especially in schools, group rules and social norms can overturn people' response to thermal stimuli. As a consequence, environmental monitorings need to be supported by exhaustive surveys to understand and represent the influence of non-physical behavioral aspects and social rules.

5. Conclusion

One of the key aims of the study was investigating the differences in behaviours in similar spaces. After analyzing window use behavior in two Hungarian school classrooms, it was found that behavior differs to a great extent. In case of classroom 1, indoor and outdoor temperatures are the key parameters that trigger users' actions on windows which is in line with current literature. However, in case of classroom 2, no statistical correlation could be found between window use and environmental parameters. As the quantitative data collection campaign was supplemented by interviews conducted with teachers using the classrooms, essential internal and social differences could be identified that were the reason between the different behavioral patterns observed in the two classrooms.

These findings formulate the need for future similar studies that investigate further both environmental and social phenomenon in case of different building types (commercial, residential spaces), preferably in different life cycle phase (before retrofit, newly renovated or new buildings). Future findings might support both the building design procedures and building use practices.

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Figure

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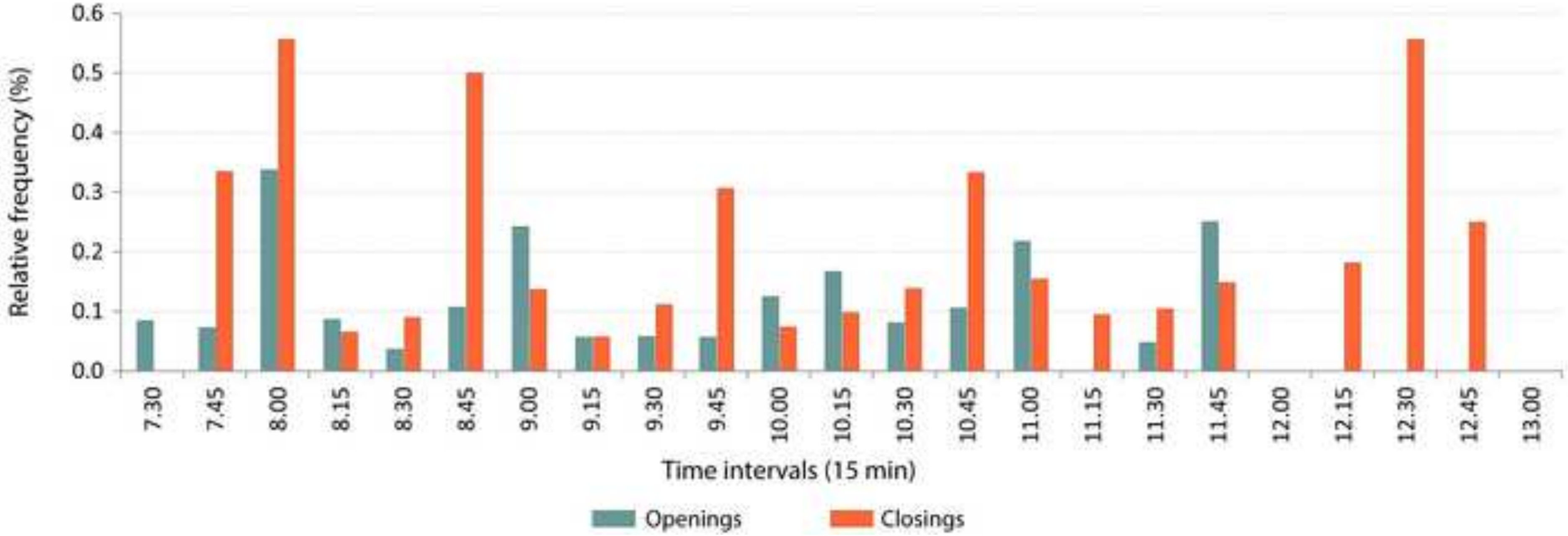

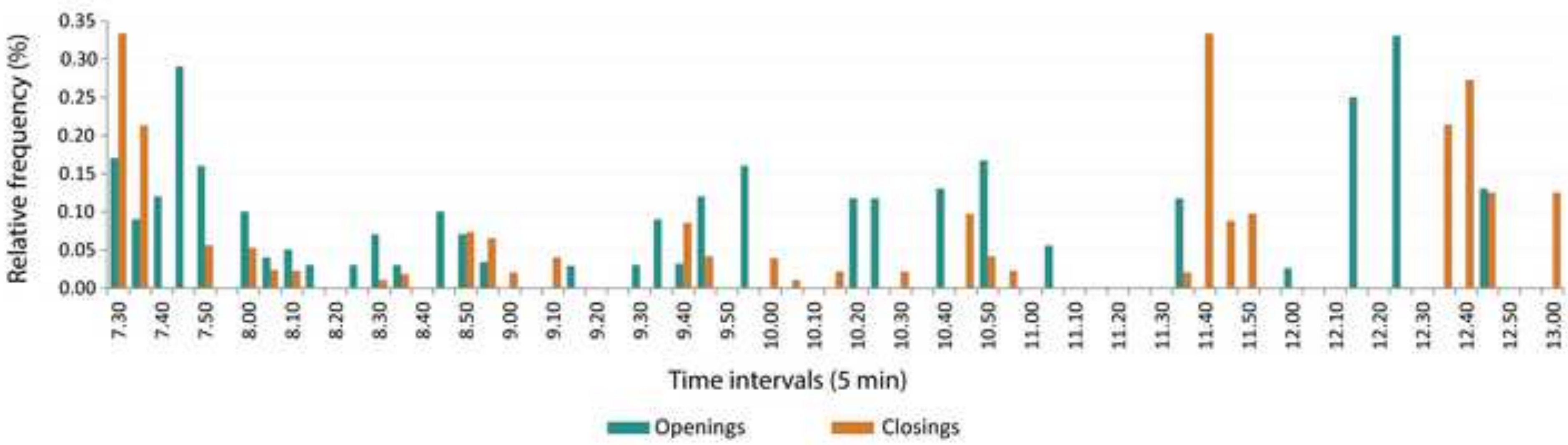
Relative frequency (%)
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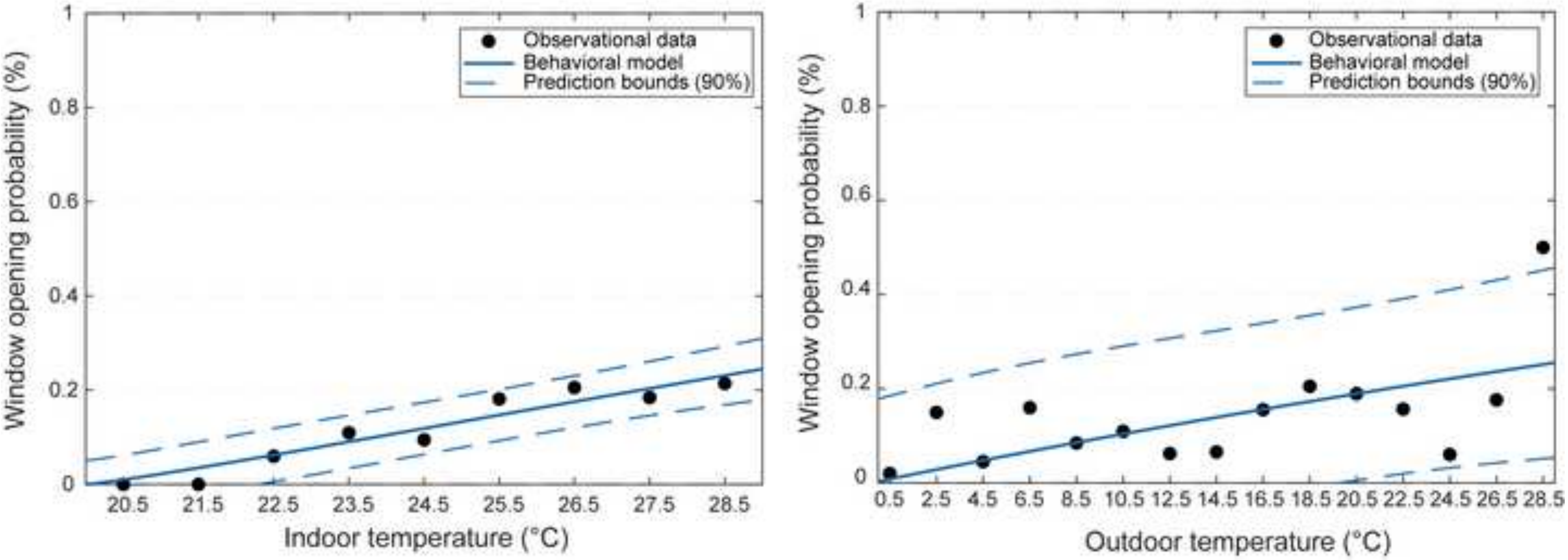
Time intervals (5 min)
Openings
Closings



1
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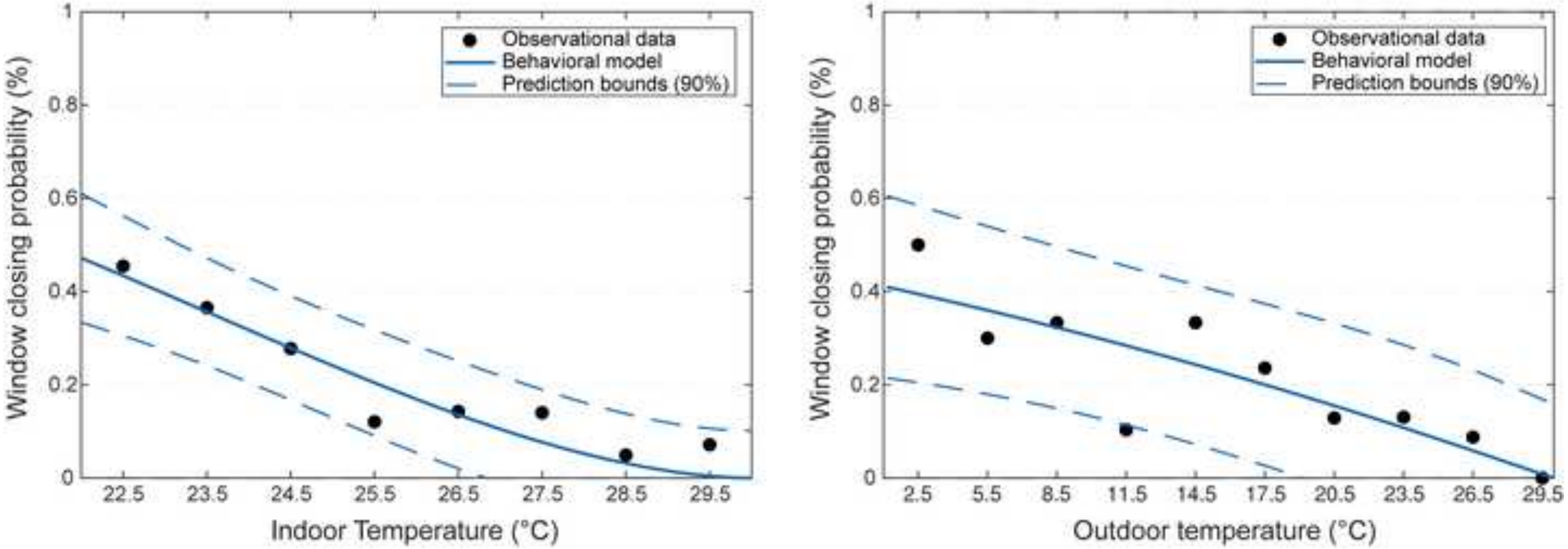
0
Window opening probability (%)
Observational data
Behavioral model
Prediction bounds (90%)
20.5
21.5
22.5
23.5
24.5
25.5
26.5
27.5
28.5
Indoor temperature (°C)
1
0.8
0.6
0.4
0.2
0
Window opening probability (%)
Observational data
Behavioral model
Prediction bounds (90%)
0.5
2.5
4.5
6.5
8.5
10.5
12.5
14.5
16.5
18.5
20.5
22.5
24.5
26.5
28.5
Outdoor temperature (°C)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Window closing probability (%)
● Observational data
Behavioral model
Prediction bounds (90%)
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Indoor Temperature (°C)
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0.6
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0.2
0
Window closing probability (%)
● Observational data
Behavioral model
Prediction bounds (90%)
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26.5
29.5
Outdoor temperature (°C)