Modeling Occupants' Behavior to Improve the Building Performance Simulation of Classrooms

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Abstract

Window operation in naturally ventilated classrooms is the only strategy for achieving proper air change rates. The modeling of the ventilation rate based on the window state implies knowledge of the window opening angle to evaluate the net exchange area. Nonetheless, the sensors most used to monitor window opening state are contact sensors, which allow only a binary state (i.e., open/close) to be devised. This work aims to investigate the effect that window opening information has on ventilation rates and building performance simulation by comparing the case in which window opening is described by the opening angle to the condition in which it is described as a binary I/O variable. A measurement campaign was conducted on six classrooms in a secondary school in Morlupo, Rome. Temperature, CO_2 concentration and relative humidity were monitored in the six classes, while temperature and relative humidity were monitored outdoors. During school time, a few students per class were asked to report information concerning the number of occupants and the opening state of windows and shutters on a discrete scale. From the data collected, an equivalent opening area was calculated, accounting for the combined opening of windows and shutters, being therefore representative of the net exchange area. Based on the original dataset, a second dataset was generated by considering binary window opening information both for windows and shutters. The two datasets were used, together with environmental data, to train behavioral models that were then fed into a building energy simulation model. The results of the simulations show that the simplified dataset causes an overestimation of the air changes and of the building energy need.

1. Introduction

Occupant behavior is commonly recognized as an influential factor when seeking explanations for the difference between the predicted performance of a building and its actual performance in post-occupancy conditions, the so-called performance gap (Shi et al., 2019).

Though most of the literature on occupant behavior focuses on residential and office buildings (Franceschini et al., 2022), the importance of studying people's behavior in educational buildings stems from the findings of the extensive literature regarding the role that ventilation plays in students' concentration, health, and performance (Bakó-Biró et al., 2012; Haverinen-Shaughnessy et al., 2015).

The drivers for human interaction with the envelope should be sought in a multi-domain approach. For instance, operating the shutters might be a consequence of glare or of direct solar radiation, and window operation might be triggered by air quality concerns, thermal comfort, or noise protection (Delzendeh et al., 2017). However, the drivers that are mostly used in occupant behavior modeling relate to the thermal and indoor air quality domains (Dai et al., 2020).

The interaction between occupants and the envelope is particularly relevant in naturally ventilated buildings, where window operation directly impacts on ventilation rates and, consequently, on indoor temperature, air quality, and finally on the building energy demand. In such buildings, the ventilation rate can be estimated from the indoor and outdoor environmental conditions and the net exchange area (EN 16798), which can be derived by the combined state of windows and shutters.

Many sensors and technologies are available to detect the window state. The ones that are most often deployed, which are relatively cheap and require low implementation effort, are contact sensors, which report a binary status (Belafi et al., 2018; Naspi et al., 2018; Park et al., 2019). Nonetheless, monitoring the opening angle besides the state might be relevant, as different opening angles determine different net exchange areas. Window opening angle can be monitored, among other methods, using accelerometers (Andersen et al., 2013), by implementing image recognition algorithms (Sun et al., 2022), or assessed through the administration of questionnaires (Kim et al., 2019).

2. Aim And Method

In this paper, a naturally ventilated school building is used as a case study to develop behavioral models devoted to window opening to be used in building performance simulations. In particular, the focus is on the impact of detailed models able to predict the window opening angle as opposed to simpler binary models. The research question is: **To which extent does detailed information on window state affect the building energy demand compared to an I/O information?**

The methodology adopted to address such question can be summarized by the following steps:

1. **Collection of experimental data**. A measurement campaign was carried out in six classrooms of a high school in Morlupo, Rome. Environmental parameters were monitored and detailed information on the state of windows and roller shutters was reported by the students.
2. **Modeling occupant behaviour.** Data were preprocessed by calculating an equivalent opening area that takes into consideration the opening of the sashes and of the roller shutters. Then, a second dataset was created by attributing a binary status to sashes and shutters, i.e., simulating the dataset that would have been collected if contact sensors were used. Two behavioral models were trained on the two datasets based on classification trees, algorithms that split the data into branches based on impurity criteria and assign, following the tree-like structure built upon predictor variables, the probability of falling within a specific class of the response variable.
3. **Simulation of building performance.** Energy modeling of a reference building was carried out using the two different behavioral models to evaluate the effects of window state information on the ventilation rate, and the overall energy performance.

In the analysis proposed, only thermal and indoor air quality environmental variables are accounted for (air temperature, relative humidity, and CO_2 concentration), as these can be predicted by means of building energy simulations.

3. The Measurement Campaign

The measurement campaign took place between January and May 2022, for a total of 17 weeks. Six classrooms were involved in the reporting activities. Students participated in a training program organized jointly by the universities involved in the project and the high school.

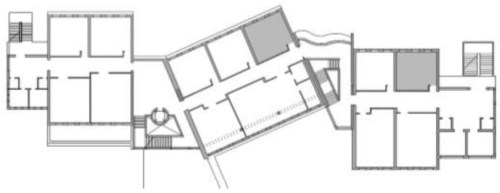
The layout of the monitored classrooms is depicted in Fig. 1 and Fig. 2. The floor surface of each classroom is 50 m² approx. Classrooms are equipped with three two-sash windows and roller shutters.

The indoor environmental conditions were monitored using HoBO MX 1102 loggers (T, RH, CO_2 concentration), which were fixed on the walls, while outdoor conditions were monitored using a HOBO U23-001A data logger (T, RH). Data acquisition was carried out with a 10-min time resolution.

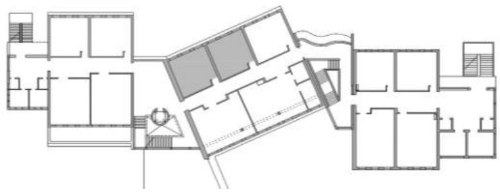
During the lecture, students were provided with printed spreadsheets in which they were asked to write down the condition of the room and the time at which any change in state occurred. The parameters that were monitored are:

- State of each window sash (0-0.5-1)
- State of each shutter (0-0.25-0.5-0.75-1)
- State of the door (0-1)
- Number of people in the classroom
- State of the lights (0-0.5-1).

(a) Ground floor



(a) First floor



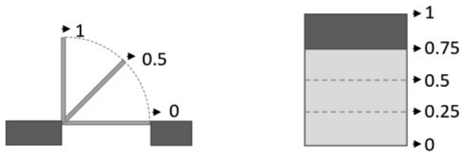
(a) Second floor

Fig. 1 – Floor plans of the IIS "Margherita Hack" in Morlupo, Rome, with indication of the classrooms involved in the project (in gray color)

Fig. 2 – Internal view of one of the classrooms that participated in the project

Fig. 3 represents the physical meaning attributed to the values that represent the state of windows and shutters. Besides the state of these elements, students also had to report the motivation that led to the interaction with the environment, by choosing from a set of pre-determined questions, and to indicate whether the request for change came from a student or from the teacher.

Each classroom managed the organization of the data collection in a different manner. Students built shifts so that each component (e.g., windows, lights, shutters, etc) was controlled by one person at a time, to ease the work and not to distract them



(a) window opening (b) shutter opening

Fig. 3 – Options available for the reporting of sashes (a) and shutters (b) status

too much from their lesson.

After these paper-based sheets were collected, they were transferred to a digital archive in which the state was reported per each time step at which an environmental measure was available, i.e., every other 10 minutes.

4. Results

4.1 Data Pre-Processing

Data were filtered by presence, to exclude data that referred to unoccupied periods from the evaluation. Only complete datasets were included in this analysis, i.e., data was excluded from the selection, when even just the state of one sash was not reported.

Starting from the information on window and shutters status, an equivalent opening area was calculated by computing, for each window, the average opening of the two sashes and by multiplying that value by the opening of the shutter. In this manner, a situation in which window sashes are open and the shutter is closed would be represented by a null equivalent opening area. This dataset will be referred to in the following as "case 1".

From the original dataset, another equivalent opening area was calculated by considering that window sashes and shutters could only assume 1/0 values. In the case of windows, values of 0.5 were then converted into 1, while in the case of shutters, values of 0.25-0.5 and 0.75 were converted into 1. Then, the equivalent opening area was calculated again, following the procedure described above. This second dataset, referred to in the following as "case 2", is characterized by a less continuous distribution of values.

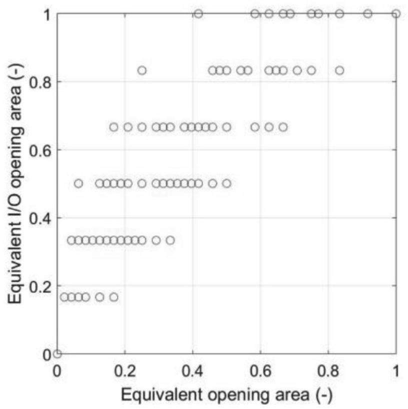


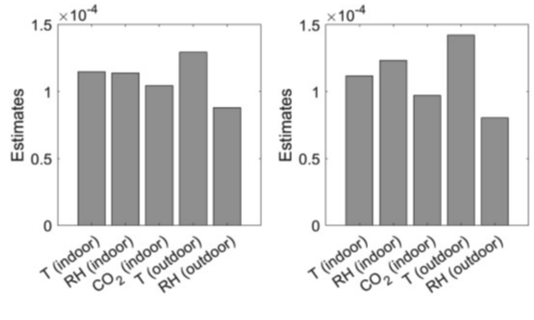
Fig. 4 – Equivalent opening areas calculated from the original dataset (case 1, x-axis) and from the modified dataset (case 2, y-axis)

The scatter plot of the equivalent opening areas calculated for case 1 and case 2 is reported in Fig. 4. The levels of equivalent opening area that are determined by the 1/0 discretization are clearly visible. As expected, in case 2 the equivalent opening area is much larger compared with the actual opening area.

4.2 Modeling Occupant Behavior

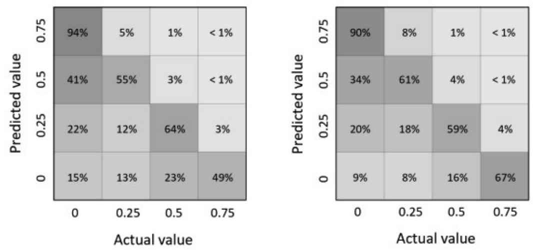
The two pre-processed datasets were then used to train behavioral models based on decision trees. To improve prediction accuracy, bagged tree classifiers were used. The equivalent opening area, binned at 25 % intervals, was assumed as the response variable, and the following predictors were used as input variables: indoor temperature, relative humidity and CO_2 concentration, outdoor temperature, and relative humidity. It is specified that the classes are very unbalanced, with a great number of occurrences related to the "closed" condition (0), and that no occurrence is found at fully open (1). This relates to the way the equivalent opening area is defined, as it is a multiplication between average opening of the window and of the shutters (which are hardly ever totally closed).

The importance of the predictors in estimating the models is reported in Fig. 5. The outdoor temperature has significant impact on both models, followed by indoor temperature and relative humidity. Outdoor humidity ranks the lowest predictor in terms of importance.



(a) Case 1 (original dataset) (b) Case 2 (I/O)

Fig. 5 – Importance of the predictors of the behavioral models



(a) Case 1 (b) Case 2

Fig. 6 – Confusion matrices of the behavioral models trained

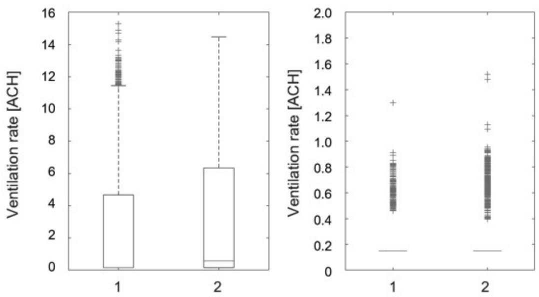
The accuracy of the models is 81.9 % and 76.5 % for case 1 (original dataset) and case 2 (I/O dataset), respectively. The confusion matrices of the two trained models are reported in Fig. 6. Green diagonals show that most of the classes are correctly identified.

The relevant share of incorrect classifications displayed in the lower left part of the diagrams indicates a tendency of both models to underestimate the equivalent opening area.

4.3 Building Performance Simulations

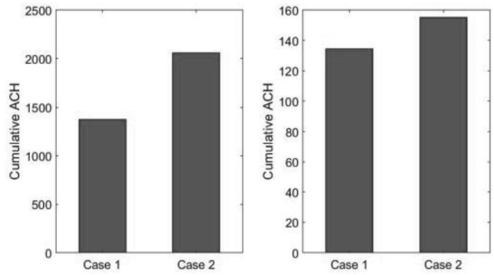
The trained models were nested in the energy simulation of a school building located in Milan. The building consisted of two classrooms with a total surface of 100 m² and 3 m high, recalling the dimensions of the classrooms in which the training dataset was collected.

The typical reference year developed in (Pernigotto et al., 2014) was used. By looping TRNSYS with Matlab, the decision tree was used as a black box that, for each time step, would read the values of the predictors (i.e., indoor temperature, relative humidity and CO_2 concentration, and the outdoor temperature and relative humidity) and attribute a class to the response variable (i.e., equivalent open-



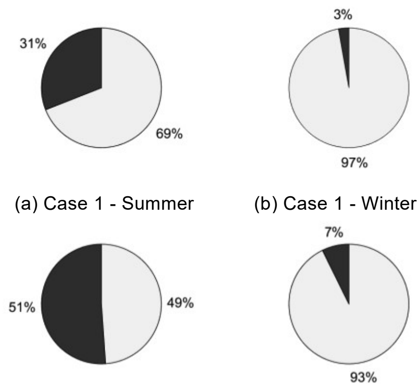
(a) summer season (b) winter season

Fig. 7 – Ventilation rate in the summer (a) and winter (b) season for case 1 and case 2



(a) Summer season (b) Winter season

Fig. 8 – Cumulative ACH calculated over the summer (a) and winter (b) season for case 1 and 2



(a) Case 1 - Summer (b) Case 1 - Winter

(c) Case 2 - Summer (d) Case 2 – Winter

Fig. 9 – Share of ventilation rates occurrences related to window opening (in purple) and to infiltration (in yellow)

ing area) based on a probabilistic approach. The information on window opening area was then used to estimate the ventilation rate based on the EN 16798 approach. A constant infiltration rate of 0.15 ACH was assumed in addition to natural ventilation to determine the overall air change rate.

All building characteristics were left unvaried in the two models (e.g., occupancy profiles, envelope characteristics, outdoor climate, etc), the different results generated by the twin simulations solely ascribable to the behavioral model called.

Fig. 7 provides a qualitative overview of the seasonal Air Changes per Hour (ACH) returned by the simulations. In the heating season (15th October-15th April), ventilation is governed by infiltration (almost no window opening). In summer, conversely, higher ventilation rates are predicted and differences among the two models arise – the number of air changes per hour being sensitively greater for case 2.

By summing up the ACH on a seasonal basis for case 1 and case 2 (Fig. 8), data displays a difference in ACH of 33 % in the summer season and a difference of 13 % in the winter season - case 2 leading to an overestimation of the ventilation rate in both cases.

Since air change rate related to infiltration is known (0.15 ACH), by data filtering it is possible to distinguish when the air change is related to infiltration or to window operation. These data are presented in Fig. 9, where the number of times in which ventilation could be attributed to infiltration or ventilation is represented as a percentage related to all observations. In case 2 (I/O opening), ventilation is generally triggered by window opening for a greater number of times compared to case 1. This effect is magnified in the summer season (51 % of occurrences related to window opening in case 2 vs 31 % in case 1).

This qualitative analysis might suffer from a bias related to the effectiveness of the window operation in the two models: in case 2, does the model predict fewer window openings because the air exchange is more effective?

The different estimates in ventilation rates affect the energy performance of the building. The energy demand in the winter season in case 1 corresponds to 1.93 MWh, while in case 2 it is 2.04 MWh, therefore indicating a 5 % increase in energy demand for case 2 in relation to case 1.

5. Discussion

The analysis carried out so far shows that there is a sensitive variation in the estimate of the air change rate when the actual window opening angle is used. In relation to the individual steps of the method proposed, some points call for further comments:

- **Experiment bound**. Occupant behavior should be dealt with as a multi-domain-driven mechanism, as multiple factors contribute to determining the interaction of individuals with the envelope. In the present study, the environmental parameters considered refer to the thermal and air quality comfort domains, through the measurement of indoor and outdoor temperature and relative humidity, and indoor CO_2 concentration. This choice was made based on the consideration that these are the features that can be controlled in building performance simulations. Multi-domain simulation would allow for a proper integration of factors.
- **Data collection.** The information of window status was reported by students and is therefore subject to accuracy issues. Errors in reporting the window and shutter states should be random (one might forget to report a window opening as well as a window closing), and therefore it might contribute to the data noisiness. In any case, this should not affect the outcome of the present study, as a comparison is proposed between the two subsets, one of which is generated based on the other. Conversely, the accuracy of data reporting might affect the accuracy of the behavioral models trained. For this reason, some of the classrooms analyzed in the present study were equipped with a device to monitor the window opening angle; data will be used in further work to test the reliability of the data reported by students.
- **Behavioral models**. The behavioral models trained show high accuracy (82 % and 76 %, respectively), but the share of false negatives is not homogeneous among classes and shows a tendency of both models to underestimate the equivalent exchange area. That might be related to the fact that samples are unbalanced. Furthermore, an extension of the original dataset both in terms of monitored states and of environmental conditions would improve the model accuracy.
- **Building performance simulation.** The results of building performance simulations show a sensitive decrease in ventilation rate when actual opening angles are considered. For the case study analyzed, this translates into an underestimate of building energy consumption by 5 %. The magnitude of this effect might be biased by building, weather and systems-related factors and will be addressed in future work.

6. Conclusion

The research aimed at understanding the impact that window opening modeling has on energy performance simulation. An experimental campaign was carried out in which environmental parameters and the detailed states of windows and shutters were monitored. Two behavioral models were trained to account for I/O opening information and the discrete dataset.

Energy performance simulations show that ventilation rate is strongly affected by the detail with which the window opening information is provided. A I/O discretization would, in general, lead to an overestimate of the ventilation rate and of the overall energy demand of the building.

Future work will concern the improvement of behavioral models, the evaluation of the uncertainty brought by behavioral models into energy simulation, the evaluation of the reliability of the data reported by the students, and the inclusion of monitoring parameters affecting the other domains of comfort as drivers for the window opening.

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