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An inquiry into the reliability of window operation models in building performance simulation

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Abstract

Given the impact of inhabitants' control actions on indoor environment and the complex nature of such interactions, sophisticated models of occupants' presence and behavior are increasingly deployed to enhance the reliability of building performance simulations. However, the use of occupant behavior models in building simulation efforts and their predictive performance in different contexts involves potentially detrimental uncertainties. To address this issue, the present study deploys long-term monitored data from an office area and its calibrated simulation model to conduct an external evaluation of a number of stochastic and non-stochastic window operation models in view of their a) potential in predicting occupants' operation of windows, and b) effectiveness to enhance the reliability of building performance simulation efforts. The results suggest that, while stochastic models can emulate the seemingly random character of occupant behaviour and provide probabilistic distributions of performance indicators, their use does not guarantee more reliable predictions. Leaving aside the large errors resulted from using such models without the necessary adjustments, stochastic window operation models overestimated the occupants' operation of windows in heating season and thus the annual and peak heating demands. However, as compared with rule-based models, the stochastic models display a better performance in window operation prediction and thermal comfort assessment in the free-running season.

Highlights

- Widely used stochastic and non-stochastic window operation models studied.
- Long-term monitored data and calibrated building model used for model evaluation.
- Effectiveness of the models to enhance thermal performance assessments examined.
- Stochastic models overestimated occupants' operation of windows in heating season.
- Stochastic models could enhance performance predictions in free running season.

1. Introduction

Occupants influence buildings' indoor environment due to their presence and operation of devices such as windows, shades, and luminaries. This circumstance is particularly relevant for the use of building performance simulation tools, which deploy models of occupants' presence and behavior to assess, among other things, energy performance, thermal comfort, and indoor air quality. However, given the complex nature of occupants' control-oriented behavior in buildings, arguably, the representation of occupants in building performance simulation falls short of models of other relevant factors such as building envelope, building systems, and climatic context.

In this context, modeling natural ventilation and the occupants' operation of windows has gained relatively high attention from the researchers. Traditionally, two approaches have been adopted within building performance simulation zone models to represent natural ventilation. These are namely, representation of natural ventilation as an estimated air change rate, and introduction of operable windows with the aid of multi-zone airflow models or coupled computational fluid dynamics engines. With operable windows in the models, the diversity profiles (temporal schedules) and user defined rules (to trigger the state transition based on one or a number of environmental parameters) have been conventionally used to govern the operation of windows. Of course, the simpler approach of user defined air change rates can also be implemented using schedules and/or rule-based controls to replicate the time-varying nature of natural ventilation in buildings.

However, since more than a decade ago, stochastic models of occupants' presence and behavior are increasingly deployed to address the complex nature of occupants' control actions in buildings and to increase the reliability of building performance simulation results. Numerous campaigns of occupants' behaviour monitoring and data mining efforts [1,2], development of a variety of occupant behaviour models, and examination of different workflows for integration of these models into building simulation tools [3,4] have been collectively contributing to enhance the representation of occupants in building performance simulation. Specifically, various stochastic models of window operation have been introduced, which consider influential occupancy events and the deriving indoor and outdoor environmental factors to capture the occupants' interactions with windows [5,6,7,8,9]. In addition, a number of studies have suggested that such stochastic models do a better job in predicting occupants' adaptive behavior and providing accurate building performance indicators [10,11,12].

From our perspective, however, sophistication of the stochastic models, and more specifically, the inherent advantage of these models over non-stochastic ones in representing the probabilistic nature of occupants' behavior has led to a misunderstanding that these models - as a whole – necessarily provide more "realistic" and "accurate" assessments of buildings' performance compared to the simple non-stochastic methods. In addition, the simple rule-based representations of occupants' control actions are considered to be "dated", as if they have no longer any use in simulation based studies. In this context, however, it should not be forgotten that existing stochastic behavioral models are predominantly derived based on rather limited sets of observational data and are not subjected to external validation in different settings [13,14]. Previous studies in the area have highlighted, on the one side, the lack of inter-comparison, and the uncertainty in the validity range of the developed models [15], and on the other side, the lack of robust algorithms for use of these models in building performance simulation [4]. In addition, as highlighted in previous publications [16,17,18], arguably, the relationship between the purpose of building performance simulation-based studies and the choice of occupancy-related models is yet not sufficiently recognized. Thus, the use of occupant behavior models in building performance simulation and their predictive potential in different contexts involves potentially detrimental uncertainties.

Given this background, in the current contribution we conduct an external evaluation of a number of stochastic and non-stochastic window operation models in view of their potential in predicting occupants' interactions with windows, and their effectiveness to enhance the reliability of thermal comfort and energy performance assessments. Toward this end, we selected an office area, for which long-term data on outdoor and indoor environment, occupancy, and window operation is available. As deployed in previous studies [19,20], such a test bed provides the required environmental and occupancy related input data to run and evaluate the window operation models with only one major shortcoming, namely disregard of the models' feedback. That is, while the outcome of window operation models in an interval (state of window) changes the inputs for the next interval (for example indoor air temperature or CO2 concentration), the measured indoor environmental parameters are resulted from the actual control actions of occupants in the monitoring period. Other words, without a "virtual" representation of the building performance, one fails to see the impact of model predictions on indoor environmental parameters and provide valid inputs for the models. Therefore, to evaluate the predictive performance of window operation models in a more convincing manner, we take advantage a calibrated simulation model of the office area in addition to the full set of required monitored data. Using the building calibrated simulation model, we also study the implications of different window operation models for simulation-based assessments of building heating energy demand and occupants' thermal comfort.

Thus, the study allows us to explore a number of essential questions with regard to the use of rule-based and stochastic window operation models: To what degree do these models predict the occupant's interaction with windows in a new setting, with and without calibration to on-site data? To which extent do the results of simulations that use rule-based window control schemes or stochastic models of window operation differ from a reference building model, which utilizes actual window operation data? Does the use of existing stochastic window operation models enhance the accuracy of simulation results, even without calibration with on-site window operation data?

2. Methods

2.1. Overview

In a nutshell, the present study deploys long-term monitored data from an office area and the calibrated simulation model of this building to conduct an external evaluation of a number of stochastic and non-stochastic window operation models with respect to a) their potential in predicting occupants' interaction with windows, and b) their effectiveness to enhance the reliability of building performance simulation results.

2.2. Empirical data for model calibration and evaluation

An office area at TU Wien (Vienna, Austria) was selected for the study including an open space with multiple workstations and a single-occupancy closed office. For the purpose of current study, we specifically focused on seven workstations, in which each occupant has access to one manually operable casement window. Only the enclosed office entails one workstation and two windows, but one of these windows is not operable (see Figure 1 for the arrangement of monitored occupants and operable windows assigned in the office area). The occupants' presence, state of windows and a number of indoor environment variables (including air temperature, humidity, and CO2 concentration) are monitored on a continuous basis. Outdoor environmental parameters (including air temperature and precipitation) are also continuously monitored via building's weather station. For the present study, we used 15-minute interval data from a calendar year (referred to as calibration period) to calibrate the coefficients of stochastic window operation models. A separate set of data obtained from another calendar year (referred to as validation period) was used to evaluate the predictive performance of the models.

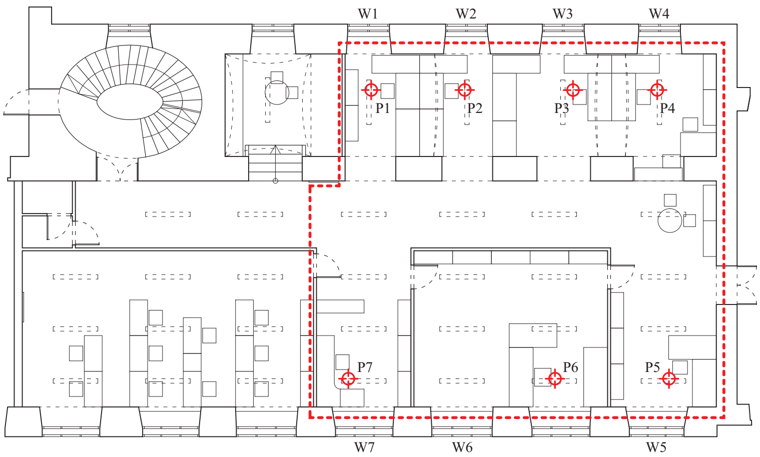

Figure 1. Schematic illustration of the office area, observed occupants (P1-P7) and operable windows (W1-W7).

2.3. Selected window operation models

We studied three existing stochastic and three simple non-stochastic window operation models. The stochastic models (referred here as A, B, and C) are derived based of occupant behavior at office buildings and are widely referenced in the building performance simulation community. They are all Markov chain based logistic regression models that estimate the probability of window opening and closing actions based on the previous window state and a number of occupancy-related and environmental independent variables. Table 1 provides a list of independent variables considered in the models. To our knowledge, at least two of these models are implemented within well-known building performance simulation tools (model A in ESP-r and model C in IDA ICE).

The non-stochastic models (referred as D, E, and F) are defined based on simple rules according to the common practice in use of building performance simulation tools without integration of stochastic models (models D and F are, for example, integrated in EnergyPlus). Model D works with an indoor temperature threshold and indoor and outdoor temperature inputs, whereas model E uses an indoor temperature dead-band together with indoor and outdoor temperature inputs to trigger window opening and closing actions. Model F, uses the comfort temperate calculated based on EN15251 as the assumed trigger of opening and closing actions.

In our study, we also included new variations of models A and C (denoted as A* and C*), as the original models did not capture a key behavioral feature in the building under study where the inhabitants are requested not to leave the windows open when they leave the office due to storm damage risk. In addition, we considered two benchmark pseudo-models (denoted as G and H), whose purpose is to put the performance of the selected models into perspective. A brief description of the aforementioned models is provided below:

- Model A, developed by Rijal et al. [6], estimates the probability of opening and closing windows based on outdoor and operative temperature, when operative temperature is outside a dead-band (Comfort temperature ± 2°C).
- Model A*, a variation of Model A, always returns a closing action upon each occupant's last departure.
- Model B, developed by Yun and Steemers [7], is derived based on summer data, and is specifically fitted to buildings without night time ventilation. It estimates the probability of opening windows upon first arrival and the probability of window opening and closing actions within intermediate occupancy interval (i.e. after first arrival and before last departure) based on indoor temperature.
- Model C, developed by Haldi and Robinson [8], estimates the probability of opening and closing actions at arrival times (first and intermediate ones), intermediate occupancy intervals, and the departure times (intermediate and last ones) based on a number of occupancy-related and environmental independent variables (see Table 1).
- Model C*, a variation of Model C, always returns a closing action upon each occupant's last departure.
- Model D, a non-stochastic model, operates as follows: windows are opened if indoor temperature is greater than outdoor temperature and indoor temperature is greater than 26 °C. Otherwise the windows are closed.
- Model E, a non-stochastic model, is formulated as follows: windows are opened if indoor temperature is greater than outdoor temperature and indoor temperature is greater than 26°C. Windows are closed if the indoor temperature is less than 22°C.
- Model F, a non-stochastic model, operates as follows: windows are opened if the operative temperature is greater than the comfort temperature calculated from the EN15251 adaptive comfort model. Following the definition of comfort temperature for free-running period in EN15251, the windows can be opened only if weighted running average of the previous 7 daily average outdoor air temperatures is above 10°C and below 30°C.
- Model G, a benchmark pseudo-model that "predicts" windows are always open.
- Model H, a benchmark pseudo-model that "predicts" windows are always closed.

It should be noted that we implemented all the models such that the opening and closing actions on each window are triggered only if the occupant associated with that window is present (see Figure 1, which illustrates the arrangement of monitored occupants and the operable windows assigned to them).

Table 1. Selected stochastic window operation models, their independent variables, and the original and calibrated estimates of coefficients

Model	Type	Occupancy phase	Independent variables and constant terms	Original coefficients	Adjusted coefficients
A	Opening & closing	-	Intercept	-6.430	-13.963 ± 1.733
			Operative temperature	0.171	0.461 ± 0.077
			Outdoor temperature	0.166	0.022 ± 0.020
B	Opening	First arrival	Intercept	-4.849 ± 1.075	-13.797 ± 1.014
			Indoor temperature	0.218 ± 0.045	0.501 ± 0.042
		Intermediate	Intercept	-0.629 ± 0.226	-11.049 ± 0.740
			Indoor temperature	0.030 ± 0.010	0.274 ± 0.031
	Closing	Intermediate	Intercept	0.209 ± 0.049	12.554 ± 1.112
			Indoor temperature	-0.007 ± 0.002	-0.651 ± 0.047
C	Opening	Arrival	Intercept	-13.700 ± 0.400	-10.120 ± 1.063
			Indoor temperature	0.308 ± 0.017	0.231 ± 0.050
			Outdoor temperature	0.040 ± 0.004	0.064 ± 0.014
			Preceding absences > 8h	1.826 ± 0.048	1.809 ± 0.130
			Occurrence of rain	-0.430 ± 0.120	-0.531 ± 0.464
		Intermediate	Intercept	-11.780 ± 0.300	-7.065 ± 1.252
			Indoor temperature	0.263 ± 0.014	0.070 ± 0.060
			Outdoor temperature	0.039 ± 0.004	0.080 ± 0.016
			Ongoing presence duration	-0.001 ± 0.000	-0.372 ± 0.076
			Occurrence of rain	-0.336 ± 0.088	0.072 ± 0.418
		Departure	Intercept	-8.720 ± 0.230	-6.101 ± 0.359
			Daily outdoor temperature	0.135 ± 0.008	0.126 ± 0.021
			Following absences > 8h	0.850 ± 0.120	NA[1]
			Ground floor	0.820 ± 0.140	NA[2]
	Closing	Arrival	Intercept	3.950 ± 0.390	3.963 ± 3.141
			Indoor temperature	-0.286 ± 0.018	-0.192 ± 0.152
			Outdoor temperature	-0.050 ± 0.005	-0.109 ± 0.040
		Intermediate	Intercept	-4.140 ± 0.240	7.044 ± 1.617
			Indoor temperature	0.026 ± 0.011	-0.323 ± 0.077
			Outdoor temperature	-0.063 ± 0.002	-0.142 ± 0.019
		Departure	Intercept	-8.680 ± 0.250	-0.337 ± 1.951
			Indoor temperature	0.222 ± 0.024	-0.049 ± 0.098
			Daily outdoor temperature	-0.094 ± 0.007	-0.066 ± 0.036
			Following absences > 8h	1.534 ± 0.077	1.587 ± 0.231
			Ground floor	-0.845 ± 0.074	NA[2]

[1] Not applicable, as in the dataset used for calibration, no window opening was observed when the following absence was longer than 8 hours.

[2] Not applicable, as the dataset used for calibration do not include any observation in a ground floor.

2.4. Office area calibrated simulation model

The office area was modeled in the building energy simulation tool EnergyPlus 8.4.0. It was assumed that the floor and ceiling surfaces of the office are adiabatic, as the office is situated between two occupied floors. In the zoning scheme, the open-plan south and north-oriented spaces were separated from the central corridor. However, using the network-based multi zone airflow model of EnergyPlus [21], the airflows across the external windows and the connected spaces were simulated. Figure 1 illustrates the building floor plan and the modeled area.

The constant input parameters governing bulk airflow simulation in the EnergyPlus model (namely open windows discharge coefficient and closed windows air mass flow coefficient) were set based on a previous model calibration effort [22]. Therein, the building model was populated with high-resolution monitored data on occupants' presence, operation of windows, use of lights and equipment as well as heat delivery rate of the building hydronic heating system to exclude the time-varying parameters from calibration procedure. Consequently, in such an ideal situation for calibration of model's constant input parameters, the discharge coefficient of open windows and the air mass flow coefficient of closed windows were subjected to an optimization-based calibration to minimize the root-mean-square deviation of simulated indoor air temperatures from measurements. Table 2 summarizes basic information about the office area energy model.

In the present study, we use the building calibrated simulation model as a test bed for evaluation of window operation models, which allows us to consider the models feedback, i.e. the impact of models' output (window states) on models' input (indoor temperature). The calibrated building model also enables us to determine the impact of window operation (and use of different window operation models) on the simulated building performance indicators. To fulfill these purposes, we needed a model that could represent the building performance in validation period with high accuracy. Therefore, we incorporated the monitored data pertaining to occupancy, plug loads, use of lights, and operation of heating system into the calibrated building model as a set of full-year data streams with a resolution of 15-minute intervals. This data set was obtained in the validation period. However, to represent the operation of internal venetian blinds, due to lack of relevant monitored data, we relied on our observations and the information received from the occupants. The resulting model, when fed with actual window operation data as the benchmark model, predicts the hourly indoor temperatures in validation year with a Normalized Mean Bias Error of 2.8% and a Coefficient of Variation of Root-Mean-Square Error of 4.8%. The low values of these indicators (which are suggested in [23] to evaluate the accuracy of calibrated simulation models) show the relatively high accuracy of model with slight overestimation of indoor temperatures.

The described building simulation model served as a basis, into which the selected window operation models were integrated, such that in each variation of the building model, the occupants' interactions with windows are represented using one of the selected window models. For each occupant in the building, individual occupancy data and zone-level indoor environmental factors are provided for the window operation model. That is, at each simulation time-step, the window model is executed separately for each occupant. We also built a benchmark model, which contained the actual operation of windows based on the monitored data obtained in the validation period.

The modeled building is not air-conditioned and it only uses a hydronic heating system to actively maintain thermal comfort in the cold season. In the model, we set the heating and free-running periods based on the measurements of the radiators' surface temperature in the validation period, according to which the free-running season starts from April 22 and ends on September 25. In this period, the building model simulates the free-floating temperatures, which result - among other things - from window opening and closing actions.

To represent the building performance in heating season, we took two approaches for our different model evaluation purposes. In one variation of the building model, which we used to evaluate the predictive potential of window operation models, the building hydronic system heating rate is incorporated into the model in a simplified manner (for calculation details see [22]). Through this basic representation of heating system, the impact of predicted window operations on indoor temperature is considered. However, in the model used to obtain building performance indicators, we defined an ideal non-limited heating system, which maintains the indoor temperature of different zones according to the measured indoor temperatures in the validation period. This approach enables us to obtain, as building performance indicator, the annual and peak heating demands to maintain the indoor temperatures preferred by occupants, and to see the impact of different window operation prediction on these performance indicators.

The described building model was exposed to the outdoor environmental conditions in the validation period, using an EnergyPlus weather data file generated from the on-site weather station measurements. The measured dataset included outdoor air temperature, air humidity, atmospheric pressure, global horizontal radiation, diffuse radiation, wind speed, and wind direction.

Table 2. Basic office area data and modeling assumptions

Building data / Modeling assumptions	Value
Net conditioned floor area [m^2]	187.6
Gross wall Area [m^2]	120.1
Average window-wall ratio [%]	26.7
Exterior walls U-value [$W.m^{-2}.K^{-1}$]	0.65
Exterior windows U-value [$W.m^{-2}.K^{-1}$]	2.79
Number of occupants [-]	7
Maximum lighting power density [$W.m^{-2}$]	4.1
Maximum equipment power density [$W.m^{-2}$]	9.9
Number of operable windows [-]	7
Windows discharge coefficient when open [-]	0.284
Windows air mass flow coefficient when closed [$kg.s^{-1}.m^{-1}$]	4.15×10^{-4}

2.5. Evaluation scenarios for window operation predictions

We take two approaches to evaluate window operation models in view of their potential in predicting the occupants' interaction with windows:

1) Use of a set of monitored data pertaining to indoor and outdoor environment as well as occupants' presence and interaction with windows. Here, the impact of window operation models' outputs on indoor environmental inputs is neglected.

2) Use of a calibrated building performance model populated with the same set of monitored data. Here, the calibrated building model simulates the impact of window operation models' outputs on indoor environmental inputs.

In the first approach, which has been adopted in previous studies [8,19,20], at each time-step the environmental input data for the models is provided from the monitored dataset. Hence, models' predictions of window states do not have any impact on the indoor environmental factors for the next time step. This circumstance represents a simplification in previous publications regarding window operation model validation. Therefore, in the second approach, we suggest additional use of a calibrated simulation model to examine, to which extent and for which kind of window operation models, an evaluation study without considering the models' feedback is reliable.

In both approaches, we evaluated the performance of window operation models to predict the inhabitants' interactions with windows for a one-year-long validation period, whereby the models are fed with monitored occupancy-related and outdoor environmental data from the same period according to their independent variables. The required indoor environmental factors, however, are provided from different sources. That is, in the first approach from the measurements in the same period, and in the second approach from the building simulation outputs.

In addition, in case of the stochastic window operation models, to conduct the evaluation in a comprehensive manner, we used both original and adjusted coefficients of the logit functions. Whereas the original coefficients are published by model developers, the adjusted coefficients are obtained from re-fitting the models to a separate set of data obtained from the building under study in the calibration period. We specify the models with original coefficients with a subscript "O" and the ones with calibrated coefficients with a subscript "C". Note that the latter option (involving the possibility of adjusting model coefficients based on observations in actual buildings) has no relevance to model deployment scenarios pertaining to building design support, but may be of some interest in operation scenarios of existing buildings. Table 1 lists the stochastic models' independent variables, and the original and adjusted estimates of their coefficients.

2.6. Evaluation statistics for window operation predictions

For the purpose of the current study, we used the following indicators to evaluate the predictive performance of window operation models:

- Fraction of correct open state predictions [%]: This is the number of correctly predicted open state intervals divided by the total number of open state intervals.
- Fraction of correct closed state predictions [%]: This is the number of correctly predicted closed state intervals divided by the total number of closed state intervals.
- Fraction of correct state predictions [%]: This is the number of correctly predicted interval states divided by total number of intervals.
- Fraction of open state [%]: This is the total window opening time divided by the observation time.
- Mean number of actions per day [d^{-1}] averaged over the observation time.
- Open state durations' median and interquartile range [hour].
- Closed state durations' median and interquartile range [hour].

From the above indictors, the *fraction of correct open state predictions* (as "true positive rate"), *fraction of open state*, *mean number of actions per day*, *median open state duration*, and *median closed state duration* have been suggested in previous studies [19,20] to evaluate the predictive performance of window operation models. We added three indictors to the previous work, namely *fraction of correct closed state predictions* to express models' state prediction performance, and the *interquartile range of open state and closed state durations* to capture the spread of window states' durations. Moreover, in addition to the conventional model evaluation based on the whole set of empirical data obtained in the validation period, we studied the window operation predictions in heating and free-running seasons separately to better analyse the models' performance.

2.7. Building performance indicators

To study the implications of using different window operation models for building performance simulation results in a systematic manner, we considered different building performance indicators in heating and free-running seasons. For the heating season, two basic building-level performance indicators were studied, namely annual and peak heating demand per floor area, which address the required heating energy to maintain the occupants' desired temperature set-points. These performance indicators are widely used in the simulation community, especially in situations where the user wishes to study the thermal performance of a building without modelling a full HVAC system. As the use of dynamic building performance simulation for the derivation of peak heating demand is not well established, we obtained three variations of peak heating demand based on 15-min and hourly integrated results as well as the 99.6th percentile of time-step heating demands. These variations allows us to better analyse the performance of window operation models in comparison with the benchmark model.

Concerning the free-running season, we obtained the minimum, average and maximum value of the free-floating indoor temperatures. In addition, we assessed the occupant thermal comfort based on EN15251 adaptive thermal comfort model. More specifically, as building performance indicators, we calculated the fraction of time that the occupants are present, but the temperature is below or above the limits defined in EN15251 adaptive comfort model for existing buildings (Category III, with an acceptable range of comfort temperature ± 4K). It should be noted that while thermal comfort indicators have been calculated for the occupied hours in the free-running season, the minimum, average and maximum free-floating temperatures are calculated regardless of occupancy states.

2.8. Implementation of window operation models

For the evaluation of window operation models without considering the models' feedback, we implemented the models in Matlab environment, in which the data pre- and post-processing, calibration of the logistic regression models and the Monte Carlo-based executions of the stochastic models could be smoothly accomplished. We implemented the models with complete set of input parameters published by the modellers. Only, given the proximity of measured indoor air and indoor surface temperatures in the present study, in implementation of Model A outside building simulation model, the operative temperature assumed to be equal to indoor temperature.

In order to evaluate the predictive performance of window operation models with their feedbacks on indoor environment, and to explore the effectiveness of these models to enhance the reliability of building performance simulation results, we implemented the models within the building simulation model using the EnergyPlus runtime language. For the implementation of the models in EnergyPlus we benefited from a study by Gunay et al. [4] and their offered public models. However, due to the different approaches in representing the occupants' diversity (using the measured occupant data and the estimated single values for models' coefficients in our study versus an artificial sample of occupants and use of randomly selected coefficients form the reported estimation errors in the other study), and a number of simplifications and modification applied on the models in the public repository, we needed to rewrite the codes to a large extent for the purpose of our study.

It is worthwhile to mention that, as far as we understood, the authors in [4] have tried to resolve some of the shortcomings in the models, whereas we tried to implement the models as exact as possible based on original publications, and to document the required modifications. An example of the model modifications applied for the study conducted in [4] is the addition of a condition to window models A and C (in case of model C only for opening actions upon arrival) that limits the applicability of the derived opening probabilities to situations that the outdoor temperature is above 15 °C. While this addition seems to improve the performance of models in winter, it does not disclose the potential large errors that could result from the deployment of the models in their original form.

As a technical issue associated with integration of window models into building simulation, it should be also noted that, to our knowledge, using EnergyPlus runtime language (or any other simulation runtime environment), input information such as *last departure time* and the *duration of following absence* could be provided for the models, only if the occupancy patterns are known before the simulation. If the occupants' presence is also predicted runtime (using another integrated stochastic model), it is not possible to detect occupancy events that depend on the later executions of the presence model. In such a case, one needs to execute the presence model before the simulation and populate the building model with new sets of required occupancy information for each Monte-Carlo run, which cannot be seen as a very smooth workflow. In our case, the monitored presence data was pre-processed using our Matlab codes and the resulting occupancy-relevant information such as last departure time and the duration of following absences were fed into the model as schedules based on external CSV files.

3. Results

3.1. Window operation predictions

The obtained values of evaluation indicators for different window operation models are given in Table 3 (without considering the models' feedback) and Table 4 (by considering the models' feedback via calibrated building performance model). These values are obtained from model executions in the whole validation period (a full calendar year). Table 5 provides the window operation indicators separately for heating and free-running seasons, obtained from the model executions within the calibrated building model. To better illustrate the performance of models in terms of different evaluation indicators, Figure 2, Figure 3, and Figure 4 show the models' prediction errors under consideration of their feedback. Note that in these Figures, models' relative error percentages are displayed in a logarithmic scale: For instance, a value of 1 read from the y-axis denotes a relative error of 10% in the evaluation indicator with reference to the benchmark. This mode of representation facilitates a better visibility of the differences in models' behavior.

3.2. Building performance indicators

Table 6 gives the obtained values for building annual and peak heating demand and Table 7 provides the indicators addressing building performance during free-running season. Figure 5 and Figure 6 compare the predicated free-floating temperatures of two set of models with those of the benchmark: Original stochastic models (A_o, B_o, and C_o) and two non-stochastic model (D and F) in Figure 5; modified stochastic models with original coefficients (A_o*, and C_o*) together with model B_o and non-stochastic models D and F in Figure 6. In addition, to provide a better understanding of peak heating demand predictions, Table 8 includes the number of open windows, office area air change rate and outdoor temperature for the interval, in which peak heating demand is predicted.

3.3. Remarks

In the aforementioned tables, the first row of values belongs to the monitored operation of windows (or the building simulation model populated with monitored window operation data). The second set of rows presents the stochastic models with original coefficients and the third set of rows includes the stochastic models with calibrated coefficients. The 4th set of rows provides the indicators for non-stochastic window operation models. The last two rows include the results of the aforementioned pseudo-models, which "predict" that the windows are always open (G) or always closed (H).

In case of stochastic models, the results are obtained via a 50-run Monte-Carlo simulation of window operation models. When a single value is given, it represents the mean value of these multiple model executions. When a range of values is provided, it denotes the mean and standard deviation of the outcomes.

Table 3. The values of evaluation statistics obtained from model executions without feedback

Models	Fraction of correct open state [%]	Fraction of correct closed state [%]	Fraction of correct states [%]	Fraction of open state [%]	Actions per day [d^{-1}]	Opening duration [hour]		Closing Duration [hour]	
						Median	IQR	Median	IQR
Observed	100.0	100.0	100.0	4.1	0.28	1.8	5.3	23.5	55.3
A_o	71.8	39.2	40.5	61.3	0.01	1180.0	2803.2	452.8	1442.3
A_o*	26.0	98.7	95.7	2.3	0.10	4.9	4.1	23.9	96.6
B_o	47.5	84.4	82.9	16.9	5.37	0.5	0.5	0.5	0.8
C_o	61.3	70.1	69.7	31.2	0.09	44.3	102.6	97.3	212.5
C_o*	22.2	97.9	94.8	2.9	0.15	4.2	4.7	76.3	157.5
A_c	80.9	46.4	47.8	54.7	0.01	1380.1	1318.2	635.0	974.1
A_c*	30.8	98.8	95.9	2.4	0.10	4.8	5.5	22.0	106.5
B_c	42.0	95.1	92.9	6.4	0.29	3.7	5.8	42.4	81.1
C_c	55.0	80.6	79.6	20.9	0.17	5.2	26.1	56.7	118.7
C_c*	33.7	97.5	94.9	3.8	0.22	3.2	5.6	54.2	110.1
D	32.0	98.7	96.0	2.6	0.35	0.8	2.3	1.8	18.0
E	51.5	97.8	95.9	4.2	0.14	7.8	5.0	17.8	48.1
F	45.3	93.7	91.7	7.9	0.95	0.8	2.8	1.0	15.0
G	100.0	0.0	4.1	100.0	0.0	8760.0	0.0	-	-
H	0.0	100.0	95.9	0.0	0.0	-	-	8760.0	0.0

Table 4. The values of evaluation statistics obtained from model executions with feedback

Models	Fraction of correct open state [%]	Fraction of correct closed state [%]	Fraction of correct states [%]	Fraction of open state [%]	Actions per day [d^{-1}]	Opening duration [hour]		Closing Duration [hour]	
						Median	IQR	Median	IQR
Observed	100.0	100.0	100.0	4.1	0.28	1.8	5.3	23.5	55.3
A_o	44.0	85.2	83.5	16.0	0.05	18.6	59.0	152.2	308.8
A_o*	47.2	96.9	94.9	4.9	0.21	5.7	5.3	22.4	66.0
B_o	41.8	88.4	86.5	12.9	5.2	0.5	0.5	0.5	0.8
C_o	54.2	78.2	77.2	23.1	0.07	37.1	91.2	133.7	313.2
C_o*	30.9	97.5	94.7	3.7	0.18	4.5	4.9	56.4	120.9
A_c	41.3	86.0	84.2	15.1	0.04	19.8	93.1	172.5	408.2
A_c*	44.4	97.5	95.3	4.2	0.18	5.4	5.4	23.6	76.2
B_c	44.6	96.4	94.3	5.3	0.31	2.8	5.9	38.3	76.3
C_c	47.9	83.9	82.5	17.4	0.16	3.7	22.8	63.0	128.5
C_c*	35.4	97.2	94.7	4.1	0.24	3.2	5.8	45.8	97.6
D	36.0	97.6	95.1	3.8	1.25	0.3	0.3	0.5	2.5
E	54.3	95.8	94.1	6.3	0.23	6.8	6.0	18.8	47.9
F	44.1	94.8	92.8	6.8	1.78	0.3	0.5	0.5	1.3
G	100.0	0.0	4.1	100.0	0.0	8760.0	0.0	-	-
H	0.0	100.0	95.9	0.0	0.0	-	-	8760.0	0.0

Table 5. Window operation indicators at heating and free-running periods from model executions with feedback

Models	Heating period			Free-running period		
	Fraction of open state [%]	Number of actions [-]	Opening duration median [h]	Fraction of open state [%]	Number of actions [-]	Opening duration median [h]
Benchmark	0.7	238.0	0.3	8.7	470.0	3.8
A_o	2.5 ± 0.2	61.6 ± 4.3	16.8 ± 0.4	33.8 ± 0.7	67.1 ± 5.7	62.2 ± 20.4
A_o*	1.2 ± 0.0	107.2 ± 5.8	3.9 ± 0.3	9.8 ± 0.1	417.6 ± 5.6	6.5 ± 0.2
B_o	11.6 ± 0.1	7459.1 ± 37.1	0.3 ± 0.0	12.9 ± 0.1	6563.3 ± 41.3	0.3 ± 0.0
C_o	6.8 ± 0.7	69.2 ± 5.5	20.4 ± 1.6	44.8 ± 2.2	112.0 ± 7.2	64.3 ± 10.7
C_o*	1.3 ± 0.1	111.9 ± 8.4	3.6 ± 0.4	6.8 ± 0.2	352.2 ± 9.2	4.8 ± 0.3
A_c	2.0 ± 0.1	47.3 ± 4.1	16.4 ± 0.5	32.5 ± 0.6	63.5 ± 3.7	80.9 ± 17.5
A_c*	0.9 ± 0.0	81.0 ± 4.8	3.6 ± 0.4	8.7 ± 0.1	378.1 ± 6.9	6.1 ± 0.2
B_c	1.3 ± 0.1	289.5 ± 12.8	1.0 ± 0.1	10.5 ± 0.2	510.6 ± 11.8	5.1 ± 0.3
C_c	3.3 ± 0.6	170.4 ± 10.1	1.2 ± 0.2	36.0 ± 1.6	250.1 ± 12.9	16.5 ± 2.7
C_c*	0.9 ± 0.1	181.5 ± 12.9	1.1 ± 0.1	8.3 ± 0.2	419.1 ± 12.6	4.9 ± 0.3
D	0.0	28.0	0.3	8.6	2997.0	0.3
E	0.1	13.0	1.0	13.9	489.0	7.5
F	1.4	937.0	0.3	13.9	3608.0	0.3
G	100.0	0.0	4992.0	100.0	0.0	3768.0
H	0	0	0	0	0	0

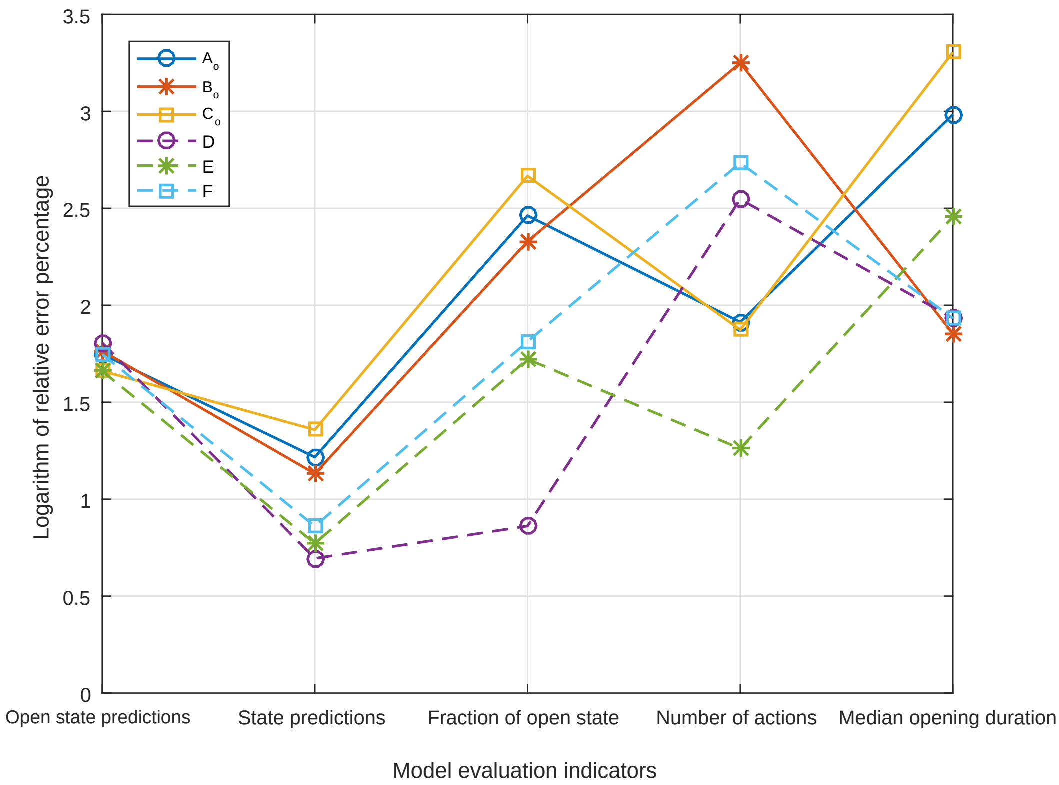

Figure 2. Errors of stochastic window operation models with original coefficients and no adjustment (A_o, B_o, and C_o) as well as non-stochastic models D, E, and F in terms of 5 evaluation statistics

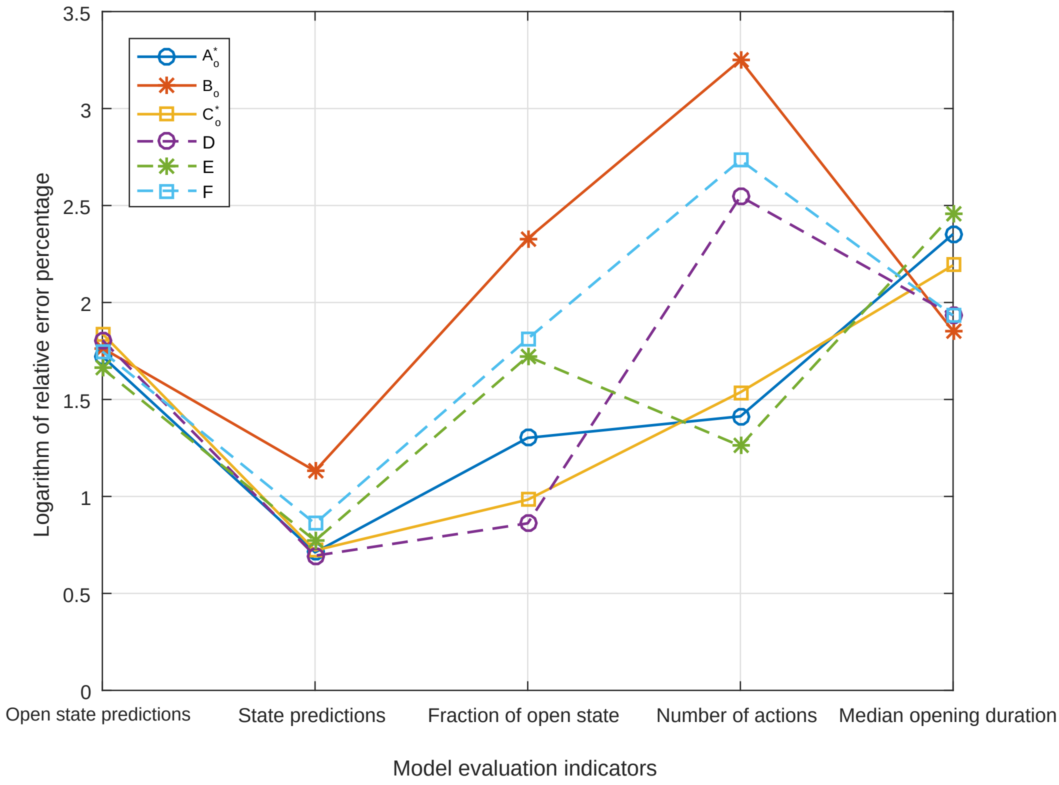

Figure 3. Errors of stochastic window operation models with original coefficients and adjusted to buildings without night time ventilation (A_o*, B_o, and C_o*) as well as non-stochastic models D, E, and F in terms of 5 evaluation statistics

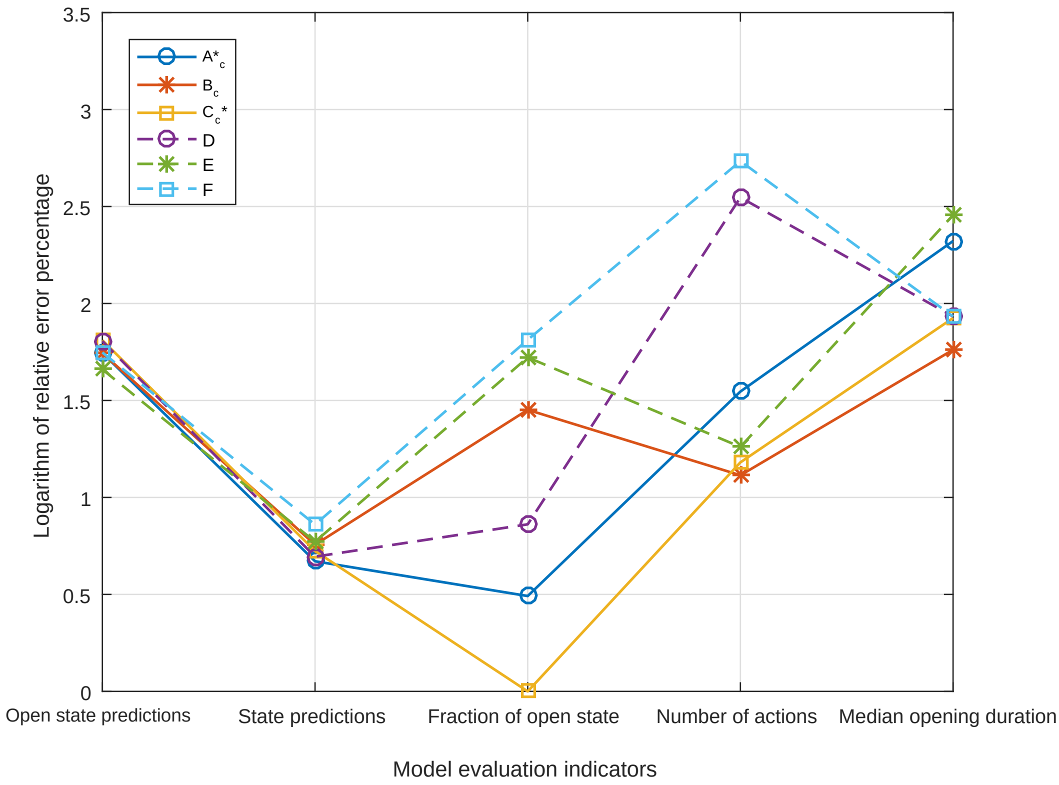

Figure 4. Errors of stochastic window operation models with calibrated coefficients and adjusted to buildings without night time ventilation (Ac*, Bc, and Cc*) as well as non-stochastic models D, E, and F in terms of 5 evaluation statistics

Table 6. Obtained values for indicators addressing building heating demand

Models	Annual [kWh.m^{-2}]	Hourly aggregated peak [W.m^{-2}]	15-min aggregated peak [W.m^{-2}]	99.6 Percentile [W.m^{-2}]
Benchmark	64.7	47.9	89.3	38.5
A_o	468.3 ± 6.2	250.5 ± 4.0	258.2 ± 3.7	222.4 ± 9.7
A_o*	68.0 ± 0.2	137.1 ± 12.7	143.1 ± 10.9	85.9 ± 4.2
B_o	142.5 ± 0.9	224.2 ± 20.8	320.7 ± 29.7	180.5 ± 3.0
C_o	135.9 ± 9.5	134.1 ± 28.1	144.1 ± 29.6	102.5 ± 20.1
C_o*	69.7 ± 1.0	92.6 ± 17.7	100.5 ± 18.6	59.3 ± 5.8
A_c	451.3 ± 13.7	245.3 ± 6.9	253.1 ± 7.5	207.1 ± 16.6
A_c*	66.1 ± 0.3	114.8 ± 17.4	120.5 ± 17.2	64.3 ± 8.2
B_c	77.8 ± 1.4	132.7 ± 23.5	148.1 ± 27.1	84.7 ± 6.0
C_c	82.0 ± 3.6	84.7 ± 15.3	96.7 ± 15.5	59.2 ± 7.8
C_c*	66.6 ± 0.5	73.2 ± 12.5	86.0 ± 14.6	48.8 ± 2.9
D	62.8	60.4	82.3	29.8
E	63.3	75.9	80.7	30.0
F	73.7	132.8	146.4	77.4
G	684.6	380.3	392.9	310.4
H	62.4	37.4	45.5	29.5

Table 7. Obtained values for indicators addressing building performance at free-running period

Models	Minimum temperature [°C]	Average temperature [°C]	Maximum temperature [°C]	Fraction below EN15251 limit [%]	Fraction above EN15251 limit [%]
Benchmark	20.4	26.8	35.9	0.0	5.5
A_o	17.6 ± 0.4	25.0 ± 0.0	35.2 ± 0.0	0.0 ± 0.0	0.6 ± 0.0
A_o*	21.5 ± 0.0	26.6 ± 0.0	35.6 ± 0.0	0.0 ± 0.0	2.7 ± 0.0
B_o	14.8 ± 0.6	25.8 ± 0.0	35.0 ± 0.2	0.2 ± 0.1	4.5 ± 0.2
C_o	15.6 ± 1.1	23.7 ± 0.2	35.2 ± 0.2	1.3 ± 0.8	0.6 ± 0.0
C_o*	19.9 ± 0.9	26.9 ± 0.0	35.9 ± 0.2	0.0 ± 0.0	7.8 ± 0.7
A_c	18.0 ± 0.5	25.1 ± 0.0	35.3 ± 0.0	0.0 ± 0.0	0.6 ± 0.0
A_c*	21.6 ± 0.0	26.7 ± 0.0	35.7 ± 0.0	0.0 ± 0.0	2.9 ± 0.1
B_c	19.4 ± 0.8	26.4 ± 0.0	35.6 ± 0.1	0.0 ± 0.0	2.9 ± 0.2
C_c	17.1 ± 1.0	24.5 ± 0.1	35.2 ± 0.2	0.1 ± 0.1	0.6 ± 0.0
C_c*	19.9 ± 1.0	26.7 ± 0.0	35.7 ± 0.2	0.0 ± 0.0	5.0 ± 0.6
D	21.7	26.6	33.4	0.0	2.8
E	20.6	26.3	35.5	0.0	2.5
F	15.8	26.1	35.3	0.0	3.5
G	10.2	21.6	35.1	26.3	0.4
H	21.6	27.8	34.9	0.0	25.0

Table 8. Number of open windows, air change rate and outdoor temperature at peak heating demand

Models	15-min aggregated Peak heating demand [W.m^{-2}]	Number of open windows at peak load [-]	Office area air change rate at peak load [h^{-1}]	Outdoor temperature at peak load [°C]
Benchmark	89.3	2	2.0	-3.4
A_o	258.2 ± 3.7	4.4 ± 1.2	8.2 ± 1.0	-2.9 ± 2.1
A_o*	143.1 ± 10.9	4.3 ± 0.8	6.3 ± 0.8	5.6 ± 2.0
B_o	320.7 ± 29.7	5.8 ± 0.6	11.2 ± 1.7	-2.0 ± 1.9
C_o	144.1 ± 29.6	4.1 ± 1.8	5.0 ± 1.4	-0.2 ± 3.4
C_o*	100.5 ± 18.6	4.7 ± 1.1	3.4 ± 1.1	1.3 ± 2.5
A_c	253.1 ± 7.5	3.0 ± 1.5	9.2 ± 1.3	-0.7 ± 2.5
A_c*	120.5 ± 17.2	3.9 ± 0.7	4.7 ± 0.9	4.2 ± 3.2
B_c	148.1 ± 27.1	3.0 ± 0.7	4.8 ± 1.1	-1.3 ± 2.6
C_c	96.7 ± 15.5	3.3 ± 1.8	3.4 ± 1.1	0.9 ± 3.9
C_c*	86.0 ± 14.6	3.7 ± 1.6	2.8 ± 0.9	0.5 ± 3.4
D	82.3	4.0	4.4	9.9
E	80.7	4.0	4.3	10.2
F	146.4	7.0	11.1	11.1
G	392.9	7.0	13.7	-2.2
H	45.5	0	0.1	7.4

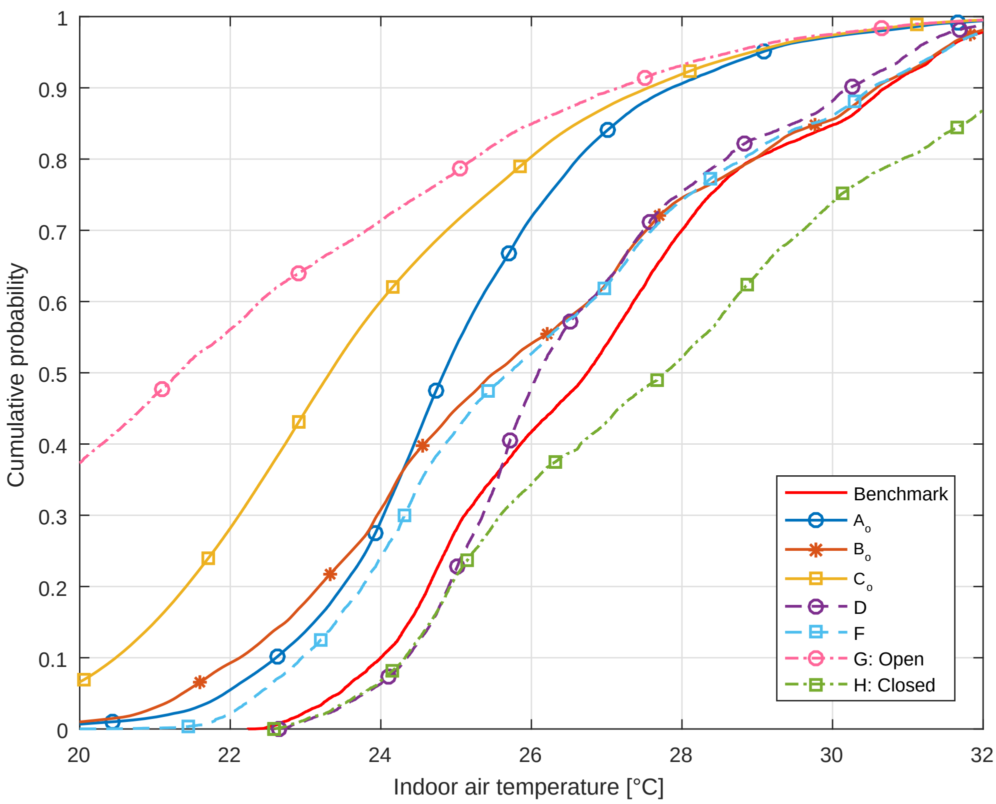

Figure 5. Cumulative distribution of free-floating temperatures obtained from stochastic models A_o, B_o, and C_o, non-stochastic models D and F, as well as benchmark and pseudo-models G and H.

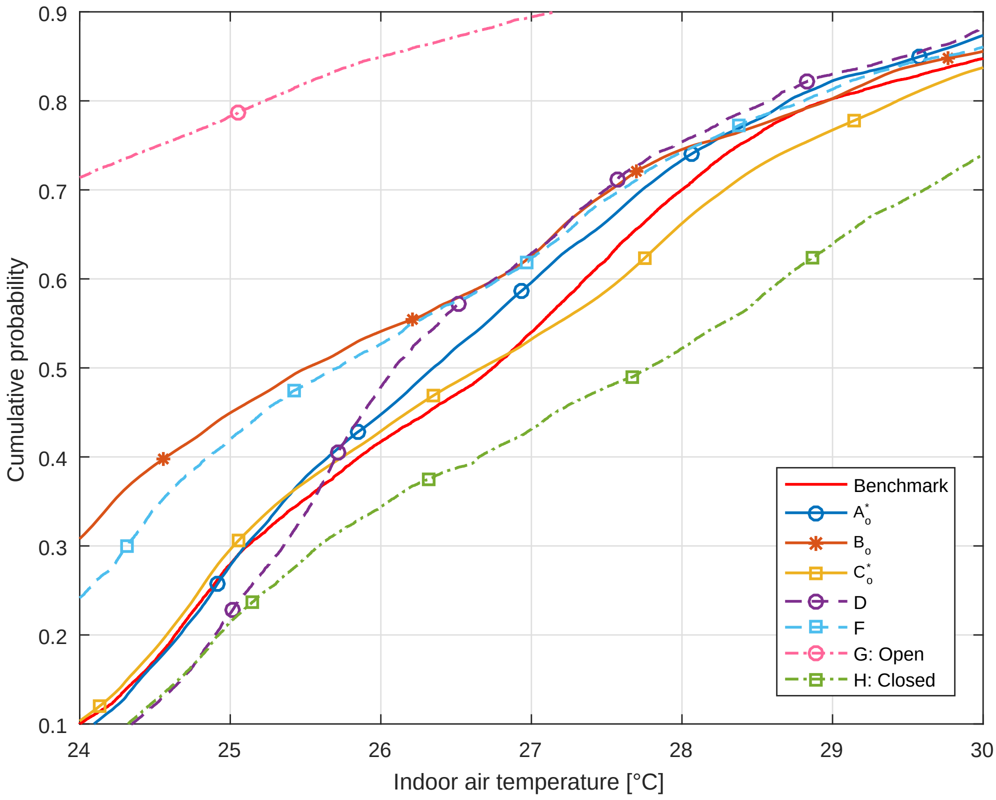

Figure 6. Cumulative distribution of free-floating temperatures obtained from stochastic models A_o*, B_o, and C_o*, non-stochastic models D and F, as well as benchmark and pseudo-models G and H.

4. Discussion

4.1. Model evaluation approaches

As mentioned before, most behavioral models use some indoor environmental data as independent variables. However, empirical evaluation of such models typically ignores action consequences for the indoor environment. To address this very problem, we conducted the evaluation using two alternatives, namely with and without inclusion of models' feedback. Given the respective results shown in Table 3 and Table 4, the models appear to perform similarly relative to each other, with and without considering their feedback. However, without considering the models' feedback (in this case, regarding the indoor temperature), the evaluation efforts can fail to provide reliable results. For example, the without-feedback evaluation method largely overestimates the fraction of open state and opening duration in model A, as the measured indoor temperatures do not fall below the dead-band defined in this model to close the windows. This tendency can be seen less dramatically in the fraction of open state predicted by model C. The disregard of models' feedback also hides the tendency of non-stochastic models D and F to predict an unrealistically large number of actions. As such, windows are operated according to these models as soon as the temperature falls below or rises above a certain threshold, which, in the realistic scenario (including feedback) would result in a large number of opening and closing actions. However, without considering the models' feedback, opening of the window does not reduce the indoor air temperature and is therefore not followed by a prompt closing action.

Given these circumstances, it can be inferred that validation efforts pertaining to window operation models (or any behavioral model with indoor environmental input), which neglect the models' feedback would be inconclusive. Therefore, the use of calibrated simulation models is more likely to provide a dependable analysis of the window operation models' performance.

4.2. Window operation predictions

A fundamental question with regard to the application of behavioral models concerns their capability in reproducing empirical observations. We may thus first ask if the models could, in the present case, provide acceptable approximations of the observations. Assuming a threshold of ±20% for the relative error of model predictions as a reasonable benchmark, we must conclude that without adjustments (night-time ventilation, calibrated coefficients), none of the studied models performs satisfactorily (see Tables 3 and 4 as well as Figure 2). Only regarding the indicator "fraction of correct state predictions" do the non-stochastic models meet this criterion. Note that the models do not appear to perform better, when we – instead of the conventional no feedback assumption (see Table 3), conduct a more realistic simulation-based test with feedback inclusion (see Tables 4). However, the nighttime ventilation adjustment markedly improves the performance of the stochastic models A_o* and C_o* (see Figure 3). Furthermore, calibrating the coefficients of stochastic models via observational data results in a significant improvement of their predictive performance. Specifically, for indicators "fraction of correct state predictions", "predicted fraction of open state", and "the number of daily actions", these models' relative errors remains roughly under 30% (see Figure 4).

More specifically, concerning the models' performance in heating and free-running seasons, the results provided in Table 5 facilitate a number of observations:

- In heating season, the stochastic models – especially with original coefficients – overestimate the fraction of open state and the duration of window openings.
- Based on the monitored data, the occupants have opened the windows more than 200 times in the heating season, but they have kept windows open for short durations (with a median opening duration of 0.25 h versus that of 3.75 h in free-running season), such that the overall fraction of open state in this period is only 0.7%. However, the studied

stochastic models, which do not distinguish between the heating and free-running seasons, could not capture this occupants' behavioural tendency in the heating season.

- In contrast, the non-stochastic models, with the exception of model F (whose assumed heating season based on EN15251 does not fully match that of the studied building) tend to disregard window operation in heating season.
- In the free-running season, leaving aside the required night-time ventilation adjustment, the stochastic models provide better predictions of occupants' interactions with windows compared to non-stochastic ones. However, the stochastic model B_o is an exception, which largely overestimates the fraction of open state and number of actions.
- The non-stochastic models fail to correctly predict the number of actions and duration of opening state in free-running season. Model E, as a non-stochastic model with dead-band, performs better than models D and F in terms of the number of actions, but overestimates the state durations.

4.3. Annual heating demand predictions

As mentioned previously, we conducted a benchmark simulation run whereby actual monitored information constituted the sole input information with regard to operation of windows in the simulation model. In the following discussion, we treat the results of this simulation model as the ground truth. As shown in Table 6, non-stochastic window operation models, with the exception of model F (which suffers from disagreement between the assumed and actual heating season), provide closer estimations of annual heating demand compared to the stochastic models with original coefficients. Among the stochastic ones, models A_o, B_o, and C_o show very large errors in annual heating demand assessment. In case of models A_o and C_o windows stay open after occupants' last departure, which contradicts the occupants' behaviour at the modelled building. With a modification of these models to force a closing action before last departure, predictions of models A* and C* get much closer to the benchmark. However, even these two models tend to somewhat overestimate annual heating demand, which is more obvious in case of original coefficients. This can be explained by larger fraction of window open state in heating season compared to actual operation of windows by occupants (Table 5). Model B, however, is originally derived based on summer data, and the obtained results show that using such a model for an annual simulation can yield very large errors in estimation of building performance indicators addressing the heating season.

4.4. Peak heating demand predictions

The peak heating demand in one year may not be the most appropriate benchmark to analyse the predictive performance of stochastic window operation models, because it only represents a single instance of possibilities in reality as opposed to probabilistic distributions of performance indicator values. Nonetheless, the corresponding results could be fairly informative for model comparison purposes. We have also provided the 99.6th percentile of heating demands to make the benchmark less affected by single events.

Considering the 15-min and hourly-integrated peak heating demand values provided in Table 6, the non-stochastic models (with the exception of model F) have provided closer values to the benchmark compared to the stochastic models with original coefficients. The 99.6th percentile of peak heating demand was underestimated by the non-stochastic models. The stochastic models, however, overestimated the 99.6th percentile of heating demand to the extent that the benchmark single value does not fall within the standard deviation of the predictions.

The overestimation of hourly aggregated peak heating demand by stochastic models can be explained by large number and long periods of coincident window openings in one-hour intervals. Whereas in the benchmark mode peak heating demand occurs at a winter early morning with 2 windows open for only one 15-min interval, the predictions show concurrent hour-long openings of 2 to 6 windows. This observation applies also to 15-min interval analyses, albeit in a less dramatic manner. To further clarify this issue, Table 8 shows the number of open windows, the office area air change rate, and the outdoor temperature at the time of peak. As can be seen from the results provided in Table 8, the stochastic models overestimate the number of coincident open windows in cold conditions. Concurrent opening of 4 out of 7 windows in on office when the outdoor temperature is around zero is rather unrealistic. This highlights the necessity for a better representation of occupants' diversity and the interrelations between occupant's control oriented actions. Obviously, the non-stochastic models perform worse in terms of the number of coincident window opening. However, as they limit window operation under cold conditions, very large errors in estimation of peak heating demand are not resulted.

4.5. Free-floating temperatures and thermal comfort assessments

According to Table 7, except for models C_o* and C_c*, the studied window operation models underestimate the occupants' discomfort in the free-running season. A number of stochastic models (B_o, C_o, and C_c) predict that the occupants operate the windows such that the zone operative temperature falls below the lower limit of EN15251 Category III, which is not the case in reality. However, the stochastic models B_o, C_o* and C_c* do a better job than the non-stochastic ones in providing realistic thermal comfort assessments in the free running season.

Non-stochastic models imply de facto an automated window operation mode. The resulting discomfort minimization is thus beyond what is realistically achievable via adaptive actions.

Concerning the predicted free-floating temperatures, the stochastic models that disregard the specific operational circumstances in the building (such as models A_o and C_o without any adjustment with regard to night-time ventilation) can yield larger errors compared to simple non-stochastic models (Figure 5). However, as shown in Figure 6, stochastic models A* and C*, which consider the unavailability of nigh-time ventilation in the studied building, provide more accurate assessments of free-floating temperatures in non-heating season, even without calibration to on-site data.

5. Conclusions

We studied a number of stochastic and non-stochastic window operation models to evaluate their predictive performance and their effectiveness to enhance the reliability of common building performance simulation results. The results suggest that the stochastic window operation models, if deployed in accordance to the operational circumstances in the buildings under study, could provide more realistic predictions of occupants' interactions with windows and thermal comfort assessments in free-running season. However, we could not infer superior performance of these models for heating demand assessments, as they could not capture the occupants' behaviour in the studied building during wintertime, which might have been motivated by energy conservation considerations. On the other hand, the non-stochastic models - despite simplifications such as neglecting the possible window openings in heating season - proved to be reliable for specific simulation queries, assessing annual heating demand being a case in point. However, predicting large number of window opening and closing actions and the inherent tendency to trigger concurrent actions hinder the non-stochastic window operation models from contributing to simulation studies in which the occupants' control over natural ventilation plays an important role.

In our view the study results have implications beyond the performance comparison of the models considered. The observed possible large deviations from reality underlines the need for clear documentation of associated uncertainties with existing window operation models in different deployment scenarios as well as development of more generally applicable occupancy-related models. Moreover, both model developers and potential users need to be careful with regard to introduction and characterization of behavioral models pertaining to inhabitants' actions in buildings. Specifically, statements concerning models' validity and overall applicability in the building delivery process require comprehensive empirical backing and careful model testing procedures.

6. Acknowledgements

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