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EXPLORING THE EFFECTIVENESS OF OCCUPANT BEHAVIOR MODELS TOWARD MORE RELIABLE BUILDING PERFORMANCE SIMULATION

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Univ.-Prof. Dipl.-Ing. Dr.techn. Ardeshir Mahdavi
E 259-3 Abteilung für Bauphysik und Bauökologie
Institut für Architekturwissenschaften

eingereicht an der
Technischen Universität Wien
Fakultät für Architektur und Raumplanung

von
Farhang Tahmasebi MSc
Matr. Nr.: 1125027
Aslangasse 2/9/8, 1190 Wien

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Zusammenfassung

Angesichts der Implikationen des Nutzerverhaltens auf das Innenraumklima und die Energieperformance von Bauwerken gibt es gegenwärtig große Bemühungen, diesen wesentlichen Teil der Charakteristik von Bauwerken zu erschließen, um zuverlässigere Vorhersagen der Gebäudeperformance mittels Simulationswerkzeugen zu erzielen. Die Eingabedaten der „Occupancy" – so der gebräuchliche Terminus für Anwesenheit der Gebäudenutzer und Ihre Interaktion mit den Gebäuden – unterliegen jedoch immer noch großen Unsicherheiten. Um dieses Problem zu adressieren, verwendet die vorliegende Arbeit Langzeitmessdaten und ein kalibriertes Gebäudesimulationsmodell, um eine Reihe von existierenden und neuartigen Occupancy-Modellen (hinsichtlich Anwesenheitsprofilen der Nutzer, der Nutzung von stromverbrauchenden Geräten und der Interaktion mit Fenstern) auf Ihre Zuverlässigkeit zu untersuchen.

Die Ergebnisse der Studie zeigen, dass stochastische Modelle hinsichtlich der Bewertung von Anwesenheit und Stromverbrauchsprofilen und –spitzen, wie auch für die Bewertung der Interaktion mit Fenstern in Perioden, wo nicht aktiv geheizt oder gekühlt wird, den regel-basierten Modellen überlegen sind. Allerdings führt diese gute Performance der stochastischen Modelle nicht automatisch zu einer genaueren Vorhersage bestimmter Gebäude-Performance Indikatoren, wie beispielsweise den jährlichen Heizwärmebedarf oder die Spitzenheizlast. Darüber hinaus zeigt sich, dass für bestimmte Applikationen, die Vorhersagen in geringen zeitlichen Intervallen benötigen, z.B. prädiktive Gebäudesteuerung, die nicht-stochastischen Modelle bessere Resultate liefern, da sie typische Verhaltens-Muster der Nutzer beinhalten.

Aus dieser Arbeit kann geschlossen werden, dass stochastische Occupancy-Modelle gut geeignet sind, den scheinbar zufälligen Charakter von Nutzerverhalten zu emulieren und entsprechende probabilistische Verteilungen von Performance-Indikatoren über die Zeit zu generieren. Die Integration der Diversität von Nutzerverhalten und sozialwissenschaftlicher Erkenntnisse in stochastische Occupancy-Modelle sowie ein klar definierter Verwendungsbereich der Modelle, kann diese zu wertvollen Bestandteilen von Gebäudesimulation machen.

Summary

Given the impact of occupants' presence and 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, use of occupancy-related 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 and a calibrated building simulation model to examine a number of existing and novel models of occupants' presence, use of electrical equipment and operation of windows. The models are evaluated in view of their potential in predicting occupants' behavior, as well as their effectiveness to enhance the reliability of building performance simulation efforts.

Specifically, the results of the study suggest that to assess the occupancy and plug load distributions and peaks, and for the purpose of window operation prediction in the free-running season, the stochastic models could outperform the typical diversity profile and rule-based models. However, the superior performance of stochastic models does not necessarily translate into more accurate estimations of common building performance indicators such as annual and peak heating demands. Moreover, for simulation deployment scenarios such as predictive building systems control, which rely on short time-interval predictions, the non-stochastic models tend to provide more accurate results, as they use typical patterns of occupants' presence and behavior.

In general terms, this dissertation concludes that stochastic occupant behavior models can emulate the seemingly random character of occupant behavior and provide probabilistic distributions of performance indicators. However, these models can contribute to enhance building performance simulations, if they delineate their scope of application and address the diversity and social context associated with occupants' control-oriented actions.

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Contents

Chapter 1.
Introduction

1.1. Motivation

Building performance simulation aims to support the design and operation of more habitable and sustainable built environments [1]. Toward this end, building simulation tools can provide rapid feedback on the performance implications of design alternatives and allow for what-if analyses to evaluate the robustness of new technologies under different operating conditions [2]. Moreover, in the past few years, research and development regarding the deployment of building performance simulation in the building operation phase has gained on momentum.

However, arguably, building performance simulation is yet to find its place in the building industry. While Clarke and Hensen [2] suggest that building performance simulation development suffers from an inappropriate emphasis on the software engineering aspects at the expense of evolution of the underlying physical models, there is also a consensus in the building performance simulation community that the present discrepancy between predicted and actual building performance is one of the main barriers toward the extended use of building simulation tools.

In this context, occupants and the approaches to model occupants in building performance models plays an important role. For occupants can largely influence the building behavior not only by their presence but also by their control oriented actions [3]. As a result, building performance simulation tools increasingly incorporate models of occupants' presence and behavior to assess, among other things, building energy performance 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 other relevant factors such as building envelope, building systems, and climatic context.

Consequently, 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 occupant behavior monitoring and data mining efforts [4,5,6], development of a variety of occupant behavior models, and examination of different workflows for integration of these models into building simulation tools [7,8] have been collectively contributing to enhance the representation of occupants in building performance simulation.

However, it can be argued that sophistication of the stochastic occupant behavior 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 building performance. In addition, the non-stochastic representations of occupants' presence and 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 [9,10]. 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 [11], and on the other side, the lack of robust algorithms for use of these models in building performance simulation [8]. In addition, as outlined in previous publications [12,13,14], the relationship between the purpose of building performance simulation-based studies and the choice of occupancy-related models is 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.

1.2. Objective

Given the aforementioned background, in the current contribution, as a first step toward enhancing the accuracy of building performance models, the potential of a sensitivity-analysis-assisted calibration of fixed physical properties of a building model is examined. Deploying this calibrated simulation model and long-term monitored data pertaining to indoor and outdoor environment as well as occupant behavior, a systematic evaluation of a number of existing and novel models of occupants' presence, use of electrical equipment and operation of windows is conducted. The models are evaluated in view of their potential in predicting occupants' behavior, as well as their effectiveness to enhance the reliability of building performance simulation efforts.

1.3. Structure

This dissertation is structured in terms of seven chapters. Chapter 2 deals with simulation model calibration as an initial effort toward enhancing the reliability of building performance simulations. The resulting calibrated simulation model also serves as a platform for evaluation of occupant behavior models in Chapter 5, whose output (e.g., window states) influences models' input (e.g., indoor temperature). Chapter 3 focuses on occupants' presence as a basis for modeling efforts pertaining to occupant behavior. In Chapter 4 two plug loads models are suggested and their potential in predicting the energy use associated with office equipment is explored. Chapter 5 studies a number of existing stochastic and non-stochastic window operation models in view of their potential in predicting occupants' interactions with windows and enhancing the simulation results. Finally, Chapter 6 discusses the research conclusions and future outlook. In addition, Chapter 7 lists the references, figures and tables.

Chapter 2.
Building simulation model calibration

2.1. Background

Research on performance simulation deployment opportunities in the building operation phase has recently gained on momentum. Specifically, simulation routines have been successfully applied in the conception and implementation of predictive methods for building systems control [15]. In the current study, the author also suggests the use of calibrated building simulation models for evaluation of occupant behavior models whose output (e.g., window states) influences models' input (e.g., indoor temperature). It is of course logically impossible to obtain empirical data matching every possible sequence of actions predicted by behavioral models. Hence, one needs to emulate building's response to behavioral impulses virtually, i.e., via building performance models. However, this necessitates a model that can reliably represent the building's behavior.

Many efforts have been made in recent years to address the challenges in calibration of over-parameterized building simulation models (see, for example, case studies in [16,17,18,19,20,21]). Reddy et al. [22,23] suggested a calibration methodology involving heuristic-based definition of a set of influential parameters and schedules, performing a coarse grid to identify a small set of promising parameters with narrower bounds of variability, conducting a guided grid search to further refine the promising parameter vector solutions, and using this set of solutions (as opposed to a single calibrated solution). Raftery et al. [24,25] suggested and demonstrated an evidence-based methodology for the calibration of building performance models, under which parameter values in the final calibrated model reference the source of information. Yanga and Becerik-Gerberb [26] examined a building energy simulation calibration framework, in which simultaneous accuracy for multiple levels of simulation (for instance, building and zone levels) is considered. Calibration procedure has also benefitted from the increasingly available building monitored data. For example, using hourly electricity sub-metering data, in [27] a bottom-up approach toward simulation model was examined.

Given this background, this chapter explores the potential of an optimization-based approach to simulation model calibration toward enhancing the reliability of building performance simulation results. The study also addresses a specific problem faced by an optimization-based simulation calibration approach: In many realistic circumstances, a large number of model input variables could be subjected to the optimization process. This large number of candidate input variables can be reduced to a certain extent via heuristically-based considerations pertaining, for example, to the knowledge domain captured in building physics. The author argues, however, that this process could be further rationalized, if one makes use of sensitivity analysis to identify a subset of the input variables most likely to influence the simulation results. Distinguishing this subset from the entire set of input variables will reduce the computational cost of the subsequent calibration process.

2.2. Methods

2.2.1. The monitored building

To explore the potential of optimization-based calibration in a realistic setting, an actual office in a building of the Vienna University of Technology was selected, which is equipped with a monitoring infrastructure (Figure 1). The monitoring infrastructure provides various streams of data, including indoor climate, weather conditions, energy delivery via the heating system, energy use for lighting and equipment, occupancy presence, and the opening state of windows and doors. Data are regularly collected with a variable frequency depending on the magnitude of changes in successive recordings.

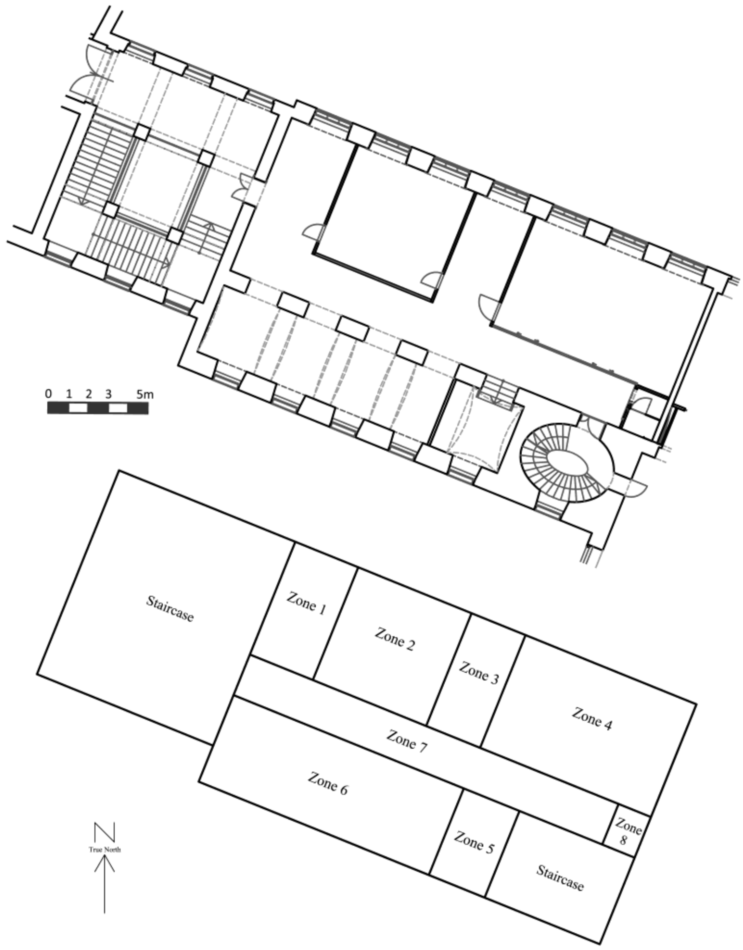

Figure 1. Building floor plan and thermal zoning of the model

The monitored data was used to: i) create a weather file based on local data instead of using a predefined "typical" year; ii) populate the initial building model with dynamic data regarding internal loads, device states, and occupancy processes; iii) calibrate the initial model (see Table 1).

Thereby, incorporation of the 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 into the model noticeably limits the calibration search space. This provides an ideal situation for identification and calibration of model's constant input parameters most likely to influence the simulation results.

Table 1. Use of monitored data in the calibration process

Use of data	Data point	Unit
Creating local weather data file	Global horizontal radiation	W/m^2
	Diffuse horizontal radiation	W/m^2
	Outdoor dry bulb temperature	^oC
	Outdoor air relative humidity	%
	Wind Speed	m/s
	Wind direction	degree
	Atmospheric pressure	Pa
Creating the initial model	Electrical plug loads	W
	State of openings (open/closed)	-
	State of the lights (on/off)	-
	Occupancy (presence/absence)	-
	Radiators' surface temperature	^oC
Calibration	Indoor air dry bulb temperature	^oC

2.2.2. The building model

The building was modeled in the whole-building energy simulation tool EnergyPlus [28]. 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 [29], the airflow between these connected spaces was simulated. Figure 1 illustrates the building floor plan and the thermal zoning of the building model.

The monitored data was incorporated as simulation input information in terms of scheduled variables. Since writing schedules manually in EnergyPlus (and probably in any other simulation program with text-based input) is a time-consuming and error-prone process, a simple program was written in Matlab [30] to generate an event-based "compact schedule" for each data point (Note that, at the time this part of study was conducted EnergyPlus did not contain the Schedule:File class).

2.2.3. The heating system model

To simulate the building's performance during the heating season, the heat delivery rate of the hydronic heating system had to be calculated and provided to the simulation model as input information. Toward this end, measured radiator surface temperatures were used. The heat emission rate of the radiators was obtained using the following equations:

$$q = q_R + q_C \tag{1}$$

$$q_R = \varepsilon \cdot \sigma \cdot A_R \cdot (T_S^4 - T_R^4) \tag{2}$$

$$q_C = h_C \cdot A_C \cdot (\theta_S - \theta_R) \tag{3}$$

$$h_c = 2 \cdot |\theta_S - \theta_R|^{0.25} + 4\varepsilon \cdot \sigma \cdot \left(\frac{T_S + T_R}{2}\right)^3 \tag{4}$$

Where:

q	heat delivery rate of radiators [W];
q_R	radiative component of heat delivery [W];
q_C	convective component of heat delivery [W];
ε	emissivity of the radiator [-];
σ	constant (5.67×10^{-8} W.m^{-2}.K^{-4});
A_R	effective radiator area for radiation [m^2];
T_S	surface temperature of radiators [K];
T_R	room temperature [K];
h_C	convective heat transfer coefficient [W.m^{-2}.k^{-1}];
A_C	effective radiator area for convection [m^2];
θ_S	surface temperature of radiator [^{o}C];
θ_R	room temperature [^{o}C].

2.2.4. Run periods

The model calibration and validation process involved a monitoring period of nearly three months consisting of two 44-day periods (Table 2). The sensitivity analysis was also performed in the calibration period.

Table 2. Specification of run periods

Run periods	Start date	End date
Calibration	15.02.2011	30.03.2011
Validation	27.04.2011	09.06.2011

2.2.5. Optimization-based calibration approach

In an optimization-based approach, calibration is cast as an error-minimizing process. In this kind of optimization problem, the cost function addresses the difference between measured and simulated data (in the present case, indoor air temperature). The variables in the optimization algorithm include a number of model input parameters. The attributes of these variables will be varied toward minimizing the cost function.

To accomplish the optimization in a way that works smoothly with the simulation model, the generic optimization program GenOpt was used. GenOpt has been developed to conveniently find the attribute range of relevant independent variables that would yield optimal system performance. GenOpt optimizes a user-supplied cost function, using a user-selected optimization algorithm [31].

The algorithm used for the optimization was the hybrid generalized pattern search and particle swarm optimization algorithm. This is one of the recommended generic algorithms for problems, where the cost function cannot be simply and explicitly stated, but can be approximated numerically by a thermal building simulation program [31].

2.2.6. Selecting calibration variables via sensitivity analysis

The problem of large search space and multiple possible solutions has been addressed in previous research (see, for example [22,32]). In the present study, 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 limit the calibration search space. In such an ideal situation for calibration of model's constant input parameters, the large number of candidate model parameters was reduced to a certain extent via heuristically-based considerations. This subset included 23 model input variables (Table 3). Secondly, to identify the input variables most likely to influence the simulation results, these variables were subjected to a Monte Carlo-based sensitivity analysis.

The performed sensitivity analysis included four steps. In the first step, assuming uniform distribution of input variables, a range was selected for each variable (Table 3). In the second step, a sample of points was generated from the distribution of the inputs using the Latin hypercube sampling method, which is a particular case of stratified sampling [33]. The result was a sequence of 690 sample elements. In the third step, the model was fed with the sample elements and a set of model outputs was produced. Since the sensitivity analysis was planned to be performed in the heating period, the building's total heat load during the run period was designated as the output.

Running 690 different models with randomly selected input parameters' values, a mapping was created from the space of the inputs to the space of the results that were used in the fourth step as the basis for sensitivity analysis. By solving a multiple linear regression model, using least squares [33], the absolute value of Standard Regression Coefficient (SRC) was calculated for the variables as a quantitative sensitivity measure. Table 4 shows the analysed variables in order of the absolute value of SRC.

Based on these results, the first four variables with SRC values higher than 0.1, were chosen to be subjected to optimization-based calibration in the next stage. These variables, their initial values and their allowed calibration ranges can be seen in Table 5.

Table 3. Variables subjected to SA and their ranges

Variables	Min. Value	Max. Value
White painted gypsum - Thermal conductivity	0.336	0.504
White painted gypsum - Density	960	1440
White painted gypsum - Thermal absorptance	0.82	0.93
White painted gypsum - Solar absorptance	0.24	0.36
White painted stucco - Thermal conductivity	0.576	0.864
White painted stucco - Density	1485	2227
White painted Stucco - Thermal absorptance	0.82	0.93
White painted Stucco - Solar absorptance	0.24	0.36
External walls brick layer - Thermal conductivity	0.56	0.84
External walls brick layer - Density	1360	2040
Wood parquet - Thermal absorptance	0.664	0.996
Wood parquet - Solar absorptance	0.48	0.72
Glazing - Solar transmittance	0.56	0.84
Glazing - Front side infrared emissivity	0.837	0.898
Glazing - Back side infrared emissivity	0.837	0.898
Glazing – Thermal conductivity	0.72	1.08
Windows frame - Thermal conductance	1.816	2.724
Outside windows discharge coefficient when open	0.64	0.96
Inside windows discharge coefficient when open	0.64	0.96
Outside closed openings air mass flow coefficient	0.00011	0.00017
Outside closed openings air mass flow exponent	0.52	0.78
Inside closed openings air mass flow coefficient	0.016	0.024
Inside closed openings air mass flow exponent	0.56	0.84

Table 4. Variables in order of absolute value of SRC

Variables	| SRC |
External walls brick layer - Thermal conductivity	0.7735
Outside windows discharge coefficient when open	0.4128
Glazing - Solar Transmittance at Normal Incidence	0.3660
Outside openings air mass flow coefficient when closed	0.1132
Glazing - Front Side Infrared Emissivity	0.0831
Inside openings air mass flow coefficient when closed	0.0760
Inside openings air mass flow exponent when closed	0.0663
Glazing - Back Side Infrared Emissivity	0.0626
White-painted Stucco - Solar absorptance	0.0592
Glazing - Thermal conductivity	0.0374
White painted gypsum - Thermal conductivity	0.0369
White painted Stucco - Thermal absorptance	0.0314
Brick - Density	0.0314
Windows frame - Thermal conductance	0.0285
White painted stucco - Thermal conductivity	0.0218
Outside openings air mass flow exponent when closed	0.0152
White painted gypsum - Thermal absorptance	0.0145
Inside windows discharge coefficient when open	0.0104
Wood parquet - Solar absorptance	0.0090
White painted gypsum - Solar absorptance	0.0058
Wood parquet - Thermal absorptance	0.0038
White painted gypsum - Density	0.0015
White painted stucco - Density	0.0010

Table 5. The variables in the first calibration

Variables	Unit	Initial value	Lower band	Upper band
External walls brick layer thermal conductivity	$W.m^{-1}.K^{-1}$	0.70	0.56	0.84
Outside windows discharge coefficient when open	-	0.80	0.00	1.0
Glazing solar transmittance at normal incidence	-	0. 837	0.56	0.85
Outside openings air mass flow coeff. when closed	$kg.s^{-1}.m^{-1}$	$1.4{\times}10^{-4}$	$1.4{\times}10^{-5}$	0.003

2.2.7. Calibration cost function

For the purpose of building performance analysis, error can be defined as the difference between a predicted value and a measured value [34]. In the present case, the error was calculated for the indoor air temperature averaged over all office zones. To minimize this error, and to maintain the "goodness of fit" of the model at the same time, a weighted function of two different indicators was defined as the cost function. The first indicator is the *Coefficient of Variation of the Root-Mean-Square Deviation* (Equations 5 & 6) which serves to aggregate the individual time step errors into a single dimensionless number.

$$RMSD = \sqrt{\frac{\sum_{i=1}^{n}(m_i - s_i)^2}{n}} \tag{5}$$

$$CV(RMSD) = \frac{RMSD}{\bar{m}} \times 100 \tag{6}$$

The other indicator used in the cost function is the *coefficient of determination* denoted by R^2. This statistic has been deployed – among other things – due to its sensitivity to extreme values (outliers). As such, it serves to moderate the building model’s overreactions to the window openings. Thus, the resulting calibrated model can be used in Chapter 5 to emulate the building response to different window operation predictions.

The coefficient of determination ranges from 0 to 1. An R^2 of 1.0 indicates that the regression line perfectly fits the data. Therefore, it is preferable to maximize the R^2 value in the optimization process. While there are different definitions of R^2, here it has been calculated via Equation 7:

$$R^2 = \left[\frac{n\sum m_i s_i - \sum m_i \sum s_i}{\sqrt{\left(n\sum m_i^2 - (\sum m_i)^2\right)\left(n\sum s_i^2 - (\sum s_i)^2\right)}}\right]^2 \tag{7}$$

In Equations 5 to 7, m_i is the measured air temperature (averaged over all office zones) at each time step, s_i is simulated air temperature at each time step, n is the total number of time steps, and $\overline{m}$ is the mean of the measured values. The defined cost function f takes into account the CV(RMSD) and R^2 in an equally weighted manner (Equation 8).

$$f_i = 0.5\, CV(RMSD)_i + 0.5\left(1 - R_i^2\right)\frac{CV(RMSD)_{ini}}{1 - R_{ini}^2} \tag{8}$$

In Equation 8, $CV(RMSD)_i$ is the coefficient of variation of the RMSD at each optimization iteration, R_i^2 is the coefficient of determination at each optimization iteration, $CV(RMSD)_{ini}$ is the coefficient of variation of the RMSD of the initial model, and R_{ini}^2 is the coefficient of determination of the initial model.

To efficiently manage the repetitive process of varying the input variables' attributes, the calculation of the cost function was tightly integrated with the simulation application. To accomplish this, the monitored indoor air temperatures were incorporated into the input stream and the EnergyPlus runtime language [35] was used to calculate the cost function by the EnergyPlus engine after each run of the model.

2.3. Results

The optimized values of the model input variables are given in Table 6. Table 7 presents the values of the indicators used in the weighted cost function, for the initial and calibrated models. Note that these results are based on the comparison of measured and simulated indoor temperatures as aggregated over all office zones.

Table 6. The optimized values of the model variables.

Variables	Unit	Optimized value
External walls brick layer thermal conductivity	$W.m^{-1}.K^{-1}$	0.561
Outside windows discharge coefficient when open	-	0.284
Glazing solar transmittance at Normal Incidence	-	0.850
Outside openings air mass flow coeff. when closed	$kg.s^{-1}.m^{-1}$	4.15×10^{-4}

Table 7. R^2 and RMSD of the initial & calibrated model.

Period	Initial Model		Calibrated Model	
	R^2	CV(RMSD)	R^2	CV(RMSD)
Calibration	0.35	4.21	0.85	3.34
Validation	0.69	8.07	0.87	2.68

2.4. Discussion

As it can be seen in Table 7, the initial model generated outputs with relatively low R^2 values in both the calibration and validation periods. The automated calibration, however, could effectively increase the R^2 value and reduce the error in terms of CV(RMSD). Thus, the present study points to the promising potential of monitoring-based optimization-assisted simulation model calibration using sensitivity analysis.

The performance of the approach could be further improved via a more detailed process for the determination of the cost function and associated weights. Note that the convergence-based approach to the definition of the values of model input parameter in the course of the optimization process does not mean that ''true values'' for such parameter are found. Rather, optimization exploits the uncertainty potential in the knowledge of exact values of such parameter to provide a better fit to the monitoring results. It is thus important, that care is taken while defining the permissible variations from the initial values of model input parameter.

In addition, considering the uncertainties in the occupancy-related time-varying parameters (and the associated large calibration search space), without the use of reliable occupants' presence and behavior models, simulation model calibration cannot contribute much toward enhancing building performance simulations. Consequently, in the following chapters the effectiveness of occupancy-related models in this regard is addressed.

Chapter 3.
Occupant presence models

3.1. Background

Occupants influence buildings' energy and indoor environmental performance due to their presence (via releasing sensible and latent heat) and operation of devices such as windows, shades, and luminaries. To quantify such influences, both empirical and simulation-aided studies have been deployed. For instance, Azar and Menassa [36] observed that energy models of office buildings' in different climatic zones in USA are highly sensitive to occupancy-related behavioral parameters. More specifically, Yang et al. [37] showed that application of HVAC schedules that use observation-based personalized occupancy profiles in a three-story office building test bed could save up to 9% energy compared to the conventional (default) schedules. As a result, building performance simulation tools deploy models of occupants' presence and behavior to represent building users' presence patterns and their control-oriented actions in the buildings.

In this context, occupants' presence models are a prerequisite for all the efforts pertaining to occupant behavior modeling. Frequently, occupancy patterns in building models are represented by typical profiles of presence probability [10]. A widely used example of such occupancy schedules for different types of buildings has been provided in ASHRAE Standard 90.1 [38]. In addition, multiple efforts are being undertaken to derive more reliable building occupancy profiles. For example, Davis and Nutter [39] used data from different sources (building security cameras, doorway electronic counting sensors, semester classroom scheduling data, and personal observations) to derive occupancy diversity profiles for six types of university buildings. Another study [40] used data obtained from 629 occupancy sensors mounted in an 11-story commercial office building to detail occupancy diversity factors for private offices, open offices, hallways, conference rooms, break rooms, and restrooms. The authors point out that the resulting diversity profiles differ as much as 46% from those published in ASHRAE 90.1, which is referenced by many energy modelers regarding occupancy diversity factors for simulations.

More recently, stochastic occupancy models have been developed and implemented to generate random non-repeating daily occupancy profiles to better capture the random nature of occupants' presence. As one of the first attempts, Newsham et al. [41] deployed the probability of first arrival and last departure as well as the probability of intermediate departures and arrivals to generate lighting profiles for a typical office. Reinhart [42] further developed this model by using the inverse transform sampling method to generate samples of arrival and departure times, and by deploying distributions of break lengths. The statistical properties of occupancy in single person offices were further examined by Wang et al. [43]. They proposed a probabilistic model to simulate occupancy in single-occupancy offices. In another effort, Page et al. [44] proposed a generalized stochastic model for the occupancy simulation using the presence probability over a typical week and a parameter of mobility (defined as the ratio of state change probability to state persistence probability). They also included long absence periods (corresponding to business trips, leaves due to sickness, holidays, etc.) as another random component in their model. Richardson et al. [45] presented a similar method for generating stochastic weekday and weekend occupancy time-series data with the aid of a matrix of transition probabilities derived from a ten-minute resolution monitoring occupancy dataset for UK households. Extending the model developed by Page et al. [44], Liao et al. [46] proposed a stochastic agent-based model of occupancy that yields time-series of the location of each agent, which is intended to provide high resolution occupancy data for building performance simulation tools.

Note that in the aforementioned studies monitored data has been used to derive a probabilistic model that generates random non-repeating daily profiles of occupancy for a long-term (e.g. annual) building performance simulation. Hence, models are suggested to perform well, if the entire set of generated random realizations of the daily occupancy profiles agrees in tendency with the monitored data over the whole simulation period. However, the agreement of the generated profiles with the monitored data (one-to-one correspondence between generated and monitored daily profiles) is not taken into consideration. Even while modelling long absences [44], the unoccupied days are scattered randomly across the year and do not necessarily match the dates of absences in the measured data. Hence, the models' performance cannot be said to have been documented (let alone validated), if the actual day-to-day prediction of occupancy and control action probabilities is relevant. Such a short-term predictive function is not a theoretical construct. Rather, it represents an essential scenario in the increasing run-time use of simulation models in the building operation phase, as practiced, for example, in model-predictive and simulation-based predictive building systems control approaches [15,47]. In these scenarios, short-term predictions of occupancy and weather are incorporated in the simulation model to predict the near-future performance of the building toward optimizing its operational regime. Thus, the level of achievable agreement between the predicted and real short-term (e.g., daily) occupancy profiles is of utmost importance.

A further issue regarding the existing probabilistic occupancy models pertains to the provided associated "validation" information. With few exceptions (see for example [46]), most of the work on evaluating the probabilistic occupancy models has focused on comparing the model outputs with the very set of data, which has been used to derive the model [3]. In the author’s view, a scientifically sound model evaluation approach must clearly separate the data segments used for model development and model assessment. This is especially important while evaluating the predictive potential of an occupancy model, which is intended to be used for operational purposes (i.e., predictive control) in buildings.

Given this background, in section 3.2 the author pursues a systematic empirically-based assessment of two previously developed probabilistic occupancy models with regard to their short-term predictive performance. To put the predictive performance of these models in context, it was compared with the performance of a simple original non-probabilistic model that also relies on past observation-based aggregated occupancy data to generate daily Boolean patterns of people's presence in buildings. The latter model was developed within the context of two ongoing EU projects [48,49] to be deployed in run-time simulations incorporated in the control logic of existing buildings.

In this context, however, an additional question concerns the implications of selecting a specific occupancy modeling approach for the accuracy of building performance simulation results. To address this question in a systematic manner, multiple studies of a variety of simulation applications are needed, whereby different performance indicators could be obtained from simulation runs while using different occupancy models. In section 3.3 the author focuses on occupants’ presence models and address the conventional use of simulation models for calculation of buildings' heating and cooling demands and peak loads. Thereby, the structure of the study (sequence of simulation runs) facilitates the exploration of a number of essential questions: To which extent do the results of simulations that use conventional diversity profiles and stochastic models of occupants’ presence differ from a reference simulation model, which utilizes extensive high-resolution observational occupancy data? Does the level of difference depend on the temporal aggregation interval of the pertinent performance indicator (e.g. annual versus hourly)? Does the use of randomly generated occupancy profiles compensate for the lack of high-resolution observational occupancy data? To address these questions, the author presents and discusses the results in view of their implications for the choice of occupants' presence models in building performance simulation.

3.2. Models' predictive potential

3.2.1. Overview

In this section, the predictive potential of two existing probabilistic occupancy models is evaluated. Moreover, their performance is compared with a simple original non-probabilistic model of occupants' presence, which was developed to be deployed in simulation-powered predictive building systems control. These models were used to generate predictions of daily occupancy profiles using the past monitoring occupancy data obtained from eight (individually monitored) workplaces in an office area at TU Wien, Vienna, Austria. One workplace is within a closed single-occupancy office, two are within semi-closed individual offices, and the rest are within an open-plan office area.

The main objective was to discern how well the models performed toward predicting daily occupancy profiles for the aforementioned eight workplaces. Model training and model evaluation were based on two separate data sets. Once trained, the models were used to predict the daily occupancy profiles of the eight workplaces for 90 working days. To evaluate the two probabilistic methods, multiple predictions were generated via a 100-run Monte Carlo execution. The comparative assessment of the models' predictive performance was accomplished with the aid of a number of pertinent statistics. Thus, the results of the study facilitate a fact-based discussion of the potential and limitations of models for the prediction of people's presence in buildings. Specifically, the results provide a proper basis toward assessing the fitness of probabilistic occupancy models in view of their incorporation potential in the building operation phase.

3.2.2. Data collection

To obtain occupancy data, wireless ceiling-mounted sensors (motion detectors) were used. The internal microprocessors of the sensors are activated within a time interval of 1.6 minutes to detect movements. The resulting data log entails a sequence of time-stamped occupied to vacant (values of 0) or vacant to occupied (values of 1) events.

To facilitate data analysis, the event-based data streams were processed to generate 15-minute interval data, using stored procedures of the MySQL database [50]. This procedure derives the duration of occupancy states (occupied/vacant) from the stored events and returns the dominant occupancy state of each interval. Occupancy periods before 8:00 and after 19:45 were not included in the study to exclude, amongst other things, the presence of janitorial staff at the offices. Occupancy data for a nine-month period (10th of November 2011 to 25th of July 2012) was used to train and compare the occupancy models.

3.2.3. First probabilistic occupancy model

The occupancy model developed by Reinhart [42] has been primarily used in Lightswitch-2002 [51] for the purpose of predicting lighting energy performance of manually and automatically controlled electric lighting and blind systems. The model uses the following probability distributions as input to capture the random nature of occupants' presence:

- The cumulative distribution function of first arrival times (CDF_a);
- The cumulative distribution function of last departure times (CDF_d);
- The probability distribution function of intermediate departure times (PDF_{id});
- The probability distribution of length of intermediate absences for morning, lunch, and afternoon periods.

A daily occupancy profile is then generated by identifying the first arrival time, last departure time, intermediate departure times, and the associated length of intermediate absences as follows:

- Using a random number between 0 and 1 (u_1), drawn from the standard uniform distribution, the first arrival time (t_a) is derived from CDF_a such that CDF_a (t_a) = u_1.
- Using a random number between 0 and 1 (u_2), drawn from the standard uniform distribution, the last departure time (t_d) is derived from CDF_d such that CDF_d (t_d) = u_2.
- To decide if an intermediate departure event occurs at a certain time (t_m), a random number between 0 and 1 (u_m) is compared with the probability of intermediate departure at that time. Once an intermediate departure is identified (PDF_{id} (t_m) $\geq$ u_m), the length of the absence is obtained randomly from the corresponding probability function of the length of intermediate absences (morning, lunch time, or afternoon).

3.2.4. Second probabilistic occupancy model

The stochastic occupancy model developed by Page et al. [44] generates random non-repeating daily occupancy profiles using the profile of presence probability and the parameter of mobility. The model has been formulated based on the hypothesis that the value of occupancy at the next time step depends on the current occupancy state and the probability of transition from this state to either the same state or its opposite state. This is reflected in Equation 9:

$$P(t+1) = P(t)T_{11}(t) + (1 - P(t))T_{01}(t) \tag{9}$$

Here, P(t+1) and P(t) are the probabilities of presence at the time steps t+1 and t, $T_{11}(t)$ is the transition probability from presence state to the same state at the time step t, and $T_{01}(t)$ is the transition probability from absence to the presence state at the time step t. In order to derive the transition probabilities based on the presence probabilities, Page et al. defined the parameter of mobility (to be provided as an input), as the ratio between the probabilities of change of the state of presence over that of no change:

$$\mu(t) = \frac{T_{01}(t) + T_{10}(t)}{T_{00}(t) + T_{11}(t)} \tag{10}$$

Here, $T_{10}(t)$ is the transition probability from presence to the absence state at the time step t, and $T_{00}(t)$ is the transition probability from absence state to the same state at the time step t. From Equations 9 and 10, and assuming the parameter of mobility as a constant, the profiles of transition probabilities can be obtained as follows:

$$T_{01}(t) = \frac{\mu - 1}{\mu + 1} P(t) + P(t+1) \tag{11}$$

$$T_{11}(t) = \frac{P(t) - 1}{P(t)} \left[\frac{\mu - 1}{\mu + 1} P(t) + P(t+1) \right] + \frac{P(t+1)}{P(t)} \tag{12}$$

Clearly, the other possible transition probabilities can be calculated via the following equations:

$$T_{00}(t) = 1 - T_{01}(t) \tag{13}$$

$$T_{10}(t) = 1 - T_{11}(t) \tag{14}$$

To generate a daily occupancy profile, the procedure starts from the first time step of the day with a vacant state for commercial buildings. Subsequently, for each time step, a random number between 0 and 1 is generated and compared with the transition probabilities to see if a change of occupancy state occurs. This is a simple case of using the inverse transform sampling method, as the cumulative distribution function of transition probabilities is a histogram of two bins. For example, if the current time step has a vacant state and the generated random number is smaller than T_{01} at that time step, the next time step is assumed to be occupied.

3.2.5. A non-probabilistic occupancy model

To support the realization of simulation-assisted building systems control approaches, a simple non-probabilistic model (referred to here as the MT model) was developed that generates daily binary occupancy profiles based on aggregated past presence data. The MT model works based on a simple procedure. The statistically aggregated daily probability profile of past presence data represents the starting point. For each time interval of the daily profile to be generated, the interval is assumed to be occupied if the associated presence probability of the aggregated past profile is higher than or equal to a specific threshold probability. Otherwise, the time interval of the daily profile is predicted to be vacant. The threshold probability is simply identified by iteratively comparing the area under the resulting predicted binary occupancy profile with the respective area under the aggregated past probability profile used for model training. Practically speaking, the best-fitting probability threshold is identified such that the area under the resulting binary occupancy profile is as close as possible to the area under the aggregated profile of probability of past presence. Figure 2 illustrates a sample aggregated profile of past presence probability, the best-fitting threshold, and the resulting Boolean occupancy profile generated by the MT model.

As the MT model does not include a stochastic term, it returns the same daily occupancy profile for any given aggregate profile of presence probability used for model training. However, if the training profile is changed (for instance, in case of training scenarios with moving temporal horizons), the generated daily profiles are updated accordingly.

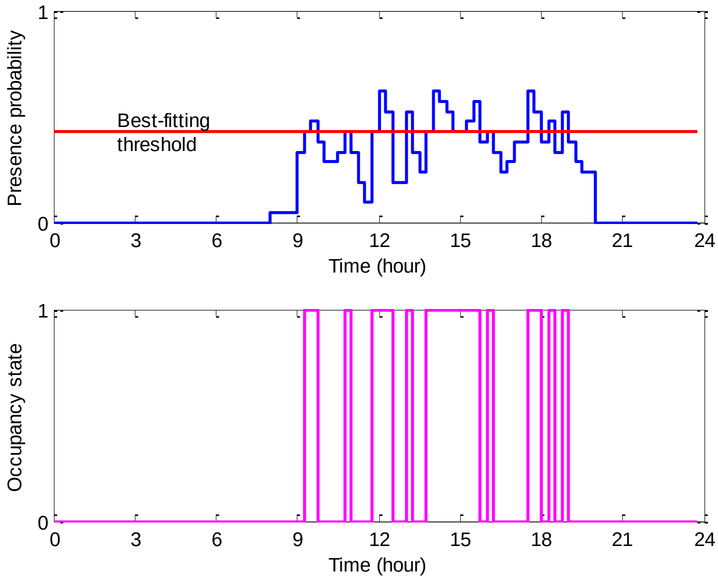

Figure 2. A presence probability profile and the best-fitting threshold (top), along with the resulting binary occupancy profile generated by the MT model (bottom).

3.2.6. Model training

Implementation of occupancy models in a continuous running mode in building control system raises a number of questions with regard to occupancy data utilization: What length of past occupancy information shall be considered for model development? Would it be advantageous to differently treat days of the week? Shall the model training occur in static or shifting intervals? In previous publications [52,53], the author examined the impact of different model training scenarios on the predictive potential of stochastic occupancy models. Concerning the number of days of monitored occupancy data as input to the model, alternatives from 5 to 20 days were examined. Days of the week were treated similarly in "All week's working days" mode and separately in "Specific week days" mode. Besides, fixed and moving training intervals were considered. In the fixed interval mode, the model was fed once with past data from a specific period and it predicted occupancy for future days. However, in the moving mode, the training interval advanced as the model predicted the occupancy day by day. Amongst other things, the results of these studies suggested that the training mode with shifting horizon offers slightly better predictions.

Thus, in the present study, a single moving training scheme was applied as follows. To generate a predicted occupancy profile for each working day, the occupancy models are fed with the monitoring occupancy data obtained from the previous 28 days. This 4-week data set is used to derive the required inputs for the aforementioned occupancy models. These are the probabilities of arrival time, departure time, intermediate departure times, and length of the intermediate absences for the Reinhart model, the presence probability profile and parameter of mobility for the Page model, and the presence probability profile for the proposed non-probabilistic model.

3.2.7. Model evaluation

To evaluate the predictive potential of models, the predicted and monitored occupancy profiles of 90 working days between the 1st of April and the 25th of July 2012 were compared. As for each run the models are fed with the occupancy data from the prior four weeks, separate sets of data are used for training and evaluating the models. To compare the performance of the models, five statistics were used:

1) First Arrival time (FA) error [hour]: The predicted minus the monitored first arrival time.
2) Last Departure time (LD) error [hour]: The predicted minus the monitored last departure time.
3) Occupancy Duration (OD) error [hour]: This metric represents the difference between the predicted and monitored daily presence duration. The presence duration was calculated by counting the number of occupied intervals.
4) Occupancy State Matching (SM) error [-]: This novel indicator represents the fraction of intervals involving false state predictions and therefore captures the mismatch between the

predicted and monitored occupancy states on a daily basis (consisting, in this case, of forty-eight 15-minute intervals between 8:00 and 19:45). For instance, if the predicted states match the monitored ones for all the 48 intervals, the value of occupancy state monitoring error would be zero. If, however, predictions would be correct for none of the intervals, the error value would be one. Another words, a value of 1 for this indicator suggests zero temporal overlap between predicted and actual occupancy states within a day. A value of zero would suggest full overlap between predicted and actual occupancy states.

5) Number of Transitions (NT) error [-]: The predicted number of daily occupied-to-vacant transitions minus the monitored number of daily occupied-to-vacant transitions.

For all models, the aforementioned statistics are calculated for each individual day during the evaluation period. However, as it would be inappropriate in case of probabilistic occupancy models to evaluate the accuracy of the predictions by comparing the results of a single run with the measurements, a 100-run Monte Carlo simulation was conducted in order to analyze the distribution of prediction errors. Given the length of validation period (90 working days) and the number of Monte Carlo runs, 9000 values for each statistic were obtained for the probabilistic models, whereas in case of the non-probabilistic model, this was limited to 90 values for each statistic.

Note that, in the present study the goal was not to predict periods of long absences due to business trips, sickness, holidays, etc. In the context of implementations pertaining to predictive building systems control, such whole-day absence instances can be presumably communicated to the building management system and reflected in the operation process. Therefore, in this contribution, only actual working days were included in the evaluation process.

3.3. Long-term performance simulation

3.3.1. Overview

To investigate the implications of using different occupants' presence models for building performance simulation results, an office area in a building of the TU Vienna was modeled, in which occupancy, plug loads, and use of electric lights have been monitored for the last three years. Using this data set, the author represented the occupants in the building model through the following modeling alternatives:

1a) Fixed diversity profiles for weekdays, Saturdays and Sundays, using ASHRAE 90.1 [38] schedules for office occupancy, lighting, and plug loads;

1b) Random daily occupancy profiles, generated by a stochastic occupancy model using model 1a occupancy schedules as input, together with proportional lighting and plug loads;

2a) Fixed observation-based average diversity profiles of occupancy, lights, and equipment for weekdays, Saturdays, and Sundays;

2b) Random daily occupancy profiles, generated by a stochastic occupancy model using model 2a occupancy schedules as input, together with proportional lighting and plug loads;

3a) Fixed observation-based individual diversity profiles of each occupant and the associated lights and equipment for weekdays, Saturdays, and Sundays;

3b) Random daily occupancy profiles, generated by a stochastic occupancy model using model 3a occupancy schedules as input, together with proportional lighting and plug loads;

4) Original year-long observational data for each occupant, light, and electrical equipment. This model has the highest resolution in

terms of occupancy and acts as a reality benchmark as far as the actual occupancy circumstances are concerned.

Note that, by a fixed diversity profile, a diversity profile (for occupancy, lighting or equipment use) is meant, which is not subjected to any stochastic process. That is, the diversity profile for weekdays, Saturdays and Sundays do not change during the annual simulation.

In addition to the above mentioned models, two “extreme” scenarios, namely empty (E) and fully occupied (F), were also defined to obtain the possible range of variations in the building performance indicators due to the variations in occupants’ presence patterns. The building annual heating and cooling demands and the peak heating and cooling loads were obtained via the sequence of simulation runs. Thereby, sensitivity of simulation results to the occupancy-related input assumptions could be systematically assessed. The information regarding the above modeling options is summarized in Table 8. Further details on the assumptions associated with the building model and occupancy modeling approaches can be found in the following sections.

3.3.2. Office area simulation model

The case study represents an office area in a university building in Vienna, Austria. This office is equipped with a monitoring infrastructure, which continuously collects data, among other things, on occupants’ presence (via wireless ceiling-mounted PIR motion detectors), plug loads, and state of the lights. For the purpose of the present study, the office area used by eight occupants, for which distinct occupancy, lighting and equipment use profiles could be obtained from the monitored data (see Figure 3), was modeled. The occupants include both academic and administrative staff, and both faculty members and graduate students. Occupants can only switch on/off luminaires affecting their workstations, as the office area does not possess any dimmable luminaires.

Table 8. Key characteristics of generated models with regard to occupancy

Model	Occupancy representation	Lighting & plug loads
E	No occupancy	No lighting and equipment use
1a	ASHRAE 90.1 schedules – Fixed	ASHRAE 90.1 schedules – Fixed
1b	ASHRAE 90.1 schedules – Randomized	Proportional to occupancy profiles
2a	Observed average schedules – Fixed	Observed average schedules – Fixed
2b	Observed average schedules – Randomized	Proportional to occupancy profiles
3a	Observed individual schedules – Fixed	Observed individual schedules – Fixed
3b	Observed individual schedules – Randomized	Proportional to occupancy profiles
4	Full-year observational occupancy data	Full-year observational lighting and equipment use data
F	Maximum occupancy during working time	Maximum loads during working time

The building was modeled in the energy simulation tool EnergyPlus v8.1. The office floor and ceiling components are set to adiabatic in the thermal model, as the office area is a middle floor in a multi-story building. Office occupants with an activity level of 120 W/person and the electric lighting and equipment with nominal installed power were defined in the model. The diversity profiles for occupants' presence and the applicable fractions of installed lighting and equipment were defined according to modeling scenarios. The building was exposed to a typical metrological year weather data for Vienna, Austria obtained from U.S. DOE weather database [54]. Table 9 summarizes basic information about the office building energy model. It should be noted that the lighting and equipment power density values presented in Table 9 refer to the maximum values (i.e. the nominal power of installed equipment), which are multiplied by the resulting diversity factors in each modeling scenario.

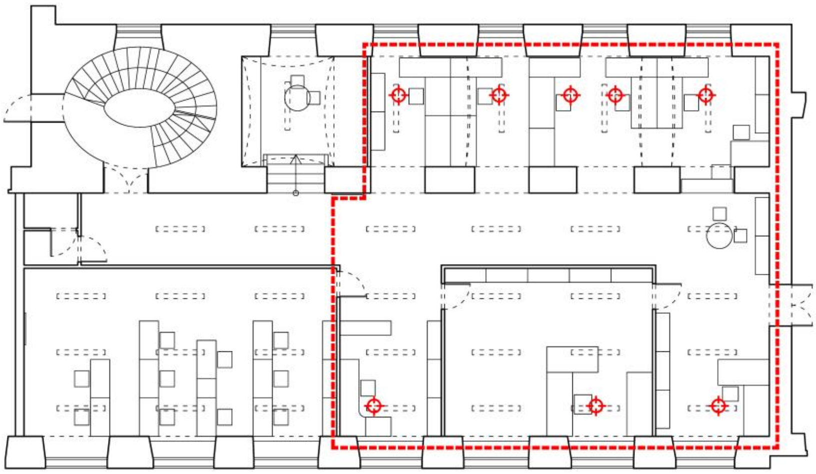

Figure 3. Building floor plan, modeled area, and position of motion detectors

Table 9. 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 [-]	8
Maximum lighting power density [$W.m^{-2}$]	4.1
Maximum equipment power density [$W.m^{-2}$]	9.9
Infiltration rate [h^{-1}]	0.20
Mechanical ventilation [$m^3.s^{-1}.Person^{-1}$]	0.007
Heating set-point [°C]	20
Cooling set-point [°C]	25
HVAC availability on weekdays	6:00 – 22:00
HVAC availability on weekends	6:00 – 18:00

3.3.3. Occupancy data collection and processing

To obtain occupancy data, wireless ceiling-mounted PIR sensors with EnOcean technology were used. The PIR sensor sends a value of 1, whenever a movement is detected. If there is no movement in its detection field, the sensor sends a value of 0 every 100 seconds. In order to facilitate data analysis, the resulting data log was processed in terms of 15-minute intervals. Toward this end, the intervals between two successive values of 1 or between a value of 1 followed by a value of 0 represent the occupied periods. Subsequently, if the duration of occupied periods within a 15-minute interval exceeds a threshold, the interval state is set to occupied. For the purpose of the current study and for all modeling scenarios, the threshold is assumed to be exceeded if the occupied phase at each interval reaches at least 50% of the interval duration. Occupancy data of a full calendar year was used to derive the observation-based presence profiles. Details on the use of occupancy data in different modeling scenarios are provided in the following sections.

3.3.4. Standard-based diversity profiles

For the modeling scenario 1a, ASHRAE 90.1 diversity profiles for office buildings were used, i.e. weekday, Saturday, and Sunday schedules for occupancy, lighting, and plug loads (Figure 4). These schedules are offered in ASHRAE 90.1 user’s manual [55] as an example of typical input data to be used in the Performance Rating Method [38] when actual schedules are not known. However, they are widely used in the building simulation community beyond their initial purpose. In model 1a, these standard-based schedules are assigned to all office occupants and the lights and electric equipment associated with their workspaces. Note that Sunday profiles were used for public holidays as well.

3.3.5. Observation-based diversity profiles

To generate observation-based diversity profiles, a one-year 15-min interval dataset on occupancy, plug loads, and state of the lights was used, which was obtained from the building monitoring infra-structure. In modeling alternative 2a, the observational data on occupants' presence, plug loads, and use of lights were averaged across all occupants. The resulting year-long data set for an average occupant was then processed to obtain a set of average profiles of presence probability, fraction of maximum lighting load, and fraction of maximum equipment load for weekdays, Saturday, as well as Sundays and public holidays (Figure 5). Neglecting diversity among occupants, the resulting average schedules were assigned to all occupants and associated lighting and equipment in the simulation model.

Model 3a was intended to consider diversity among occupants. Therefore, the weekday, Saturday, and Sunday average schedules were generated for each individual occupant, electric outlet and light switch and assigned to the corresponding objects in the simulation model. Figure 6 illustrates the observed individual diversity profiles for weekday occupancy, lights, and plug loads. Note that, to derive the diversity profiles for models 2a and 3a, vacation days were not excluded. Therefore, the resulting profiles implicitly represent the vacations.

In modeling scenario 4, however, the year-long observational data was incorporated into the simulation model. That is, instead of using typical schedules for weekdays and weekends, occupancy states, state of the lights, and the plug loads are retrieved from the monitored interval data streams at each time-step of the annual simulation. Therefore, simulation model 4 acts as a reference, as it has the highest resolution in terms of occupancy and is entirely observation-based. In other words, this option represents the reality benchmark, as far as the actual occupancy circumstances are concerned.

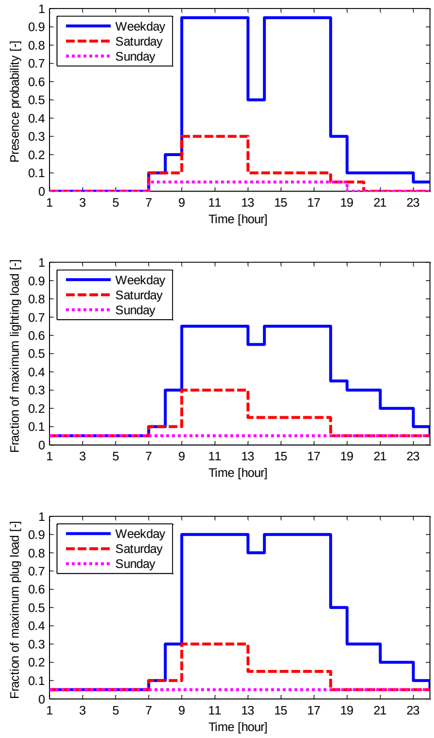

Figure 4. ASHRAE 90.1 schedules for occupancy (top), lights (middle), and plug loads (bottom) used in modeling scenario 1a.

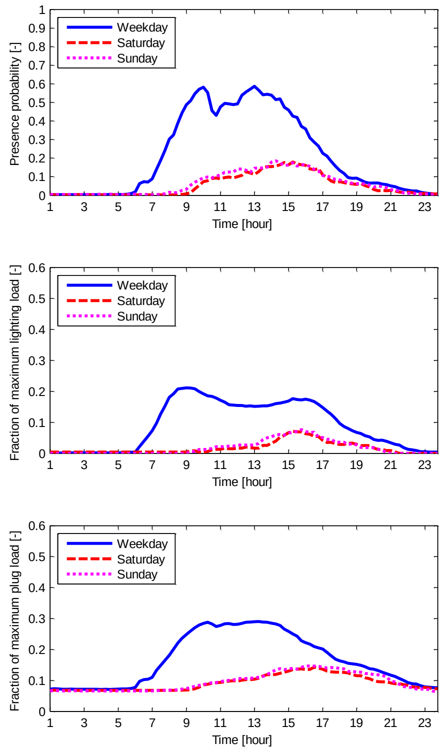

Figure 5. Observed average diversity profiles for occupancy (top), lights (middle), and plug loads (bottom) used in modeling scenario 2a.

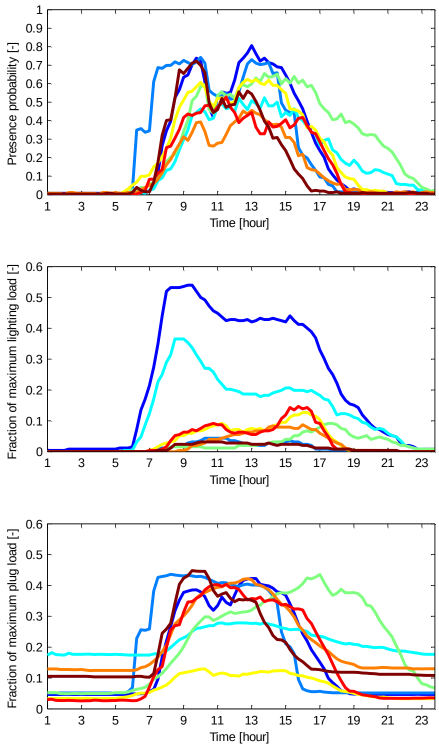

Figure 6. Observed individual diversity profiles for weekday occupancy (top), lights (middle), and plug loads (bottom) used in modeling scenario 3a.

3.3.6. Random occupancy profiles and associated loads

To represent occupants' presence in models 1b, 2b and 3b probabilistically, the stochastic occupancy model developed by Page et al. [44] was used. This model uses as input a profile of presence probability and parameter of mobility (defined as the ratio of state change probability to state persistence probability) and returns random non-repeating daily profiles of occupancy states (present or not present).

As explained in more details in Section 3.2.4, this model has been formulated based on the hypothesis that the value of occupancy at each time step depends on the previous occupancy state and the probability of transition from this state to either the same state or its opposite state. To generate a daily occupancy profile, the procedure starts from the first time step of the day with a vacant state for commercial buildings.

Subsequently, for each time step, a random number between 0 and 1 is generated and compared with the transition probabilities (which have been calculated using the input occupancy profile and parameter of mobility) to see if a change of occupancy state occurs. This is a simple case of using the inverse transform sampling method.

In order to generate random non-repeating profiles of occupancy states for models 1b, 2b, and 3b, the fixed occupancy profiles used in models 1a, 2a, and 3a were provided respectively as input for the stochastic model. The stochastic occupancy model 365 times to obtain year-long random daily presence profiles for each occupant. The occupancy profiles for weekdays, Saturdays, Sundays, and public holidays were input to the model in the right order, such that the days of the week are consistent in models with fixed and random occupancy profiles. The resulting schedules (each a column vector of 0 and 1 with length of 35040) were incorporated into the simulation models and were referenced by People objects. Note that in models 1b and 2b same set of occupancy profiles is randomized for all occupants, whereas in model 3b the stochastic model randomizes a unique set of occupancy profiles for each occupant. The parameter of mobility was set to 0.5 for all model executions in scenarios 1b and 2b. In scenario 3b this parameter was calculated for each occupant using year-long observational data, providing inputs for the stochastic model with the highest precision.

It should be noted that, for the purpose of the current study, the author did not explicitly include vacations in any of the modeling scenarios, but the average occupancy profiles implicitly represented long absences. Therefore, the "long absence" component of the above-mentioned stochastic occupancy model was also not implemented.

As for lighting and equipment use, note that even though the focus of this study is on the implications of occupants’ presence models for simulation results, the presence of occupants is not assumed to be totally irrelevant to equipment and lighting usage. However, the representation of the corresponding relationship is intentionally kept as simple as possible. To generate lighting and plug load schedules according to the randomly generated occupancy states, the applicable fraction of installed lighting and electric equipment - when each occupant is present - was calculated. In addition, the electric loads, which were not dependent on the occupants' presence, had to be considered. Therefore, in simulation models 1b, 2b, and 3b, lighting and plug loads were defined in two parts: base load and occupancy-dependent load. The base loads' fractions were identified from the fixed light and plug loads schedules used in each modeling scenario as the constant fraction of loads during the night. The remaining lighting and plug loads' fractions were assumed to be proportional to occupancy level. In detail, the applicable fractions of lighting and plug loads for each occupant were defined as the ratio of occupancy-dependent lighting or equipment loads' diversity factors to the presence probability at each time step, both obtained from the fixed schedules used for that occupant.

3.3.7. Metrics for evaluation of simulated occupancy patterns

Before exploring the implications of different occupancy modeling options for building performance simulation results, the occupancy model outputs are briefly compared with the actual occupancy levels (represented in Model 4), so that the implications of these scenarios for simulation results could be better understood.

Toward this end, the predicted fractions of maximum occupancy at the building level derived from the incorporated fixed or random occupancy profiles were examined. To conduct a quantitative evaluation, 3 metrics were considered, namely Mean Error, Root Mean Squared Error (RMSE), and Jensen-Shannon Distance.

Mean Error and RMSE were used to track time-step differences between the predicted and measured occupancy levels. These metrics were obtained using the following equations:

$$Mean\ Error = \frac{\sum_{t=1}^{n}\left(BOF_p(t) - BOF_r(t)\right)}{n} \tag{15}$$

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}\left(BOF_p(t) - BOF_r(t)\right)^2}{n}} \tag{16}$$

Here, $BOF_p(t)$ is the predicted building-level occupancy fraction at time-step t, $BOF_r(t)$ is the reference building-level occupancy fraction at time step t (obtained from model 4), and n is the number of simulation time-steps in a year, which equals 35040.

In addition, to compare the distribution of predicted occupancy levels with the distribution of occupancy levels obtained from the reference case, the square root of Jensen–Shannon divergence was utilized. This metric is used to compute distances between two probability distributions. For two probability distributions P and Q, Jensen-Shannon divergence (JSD) is calculated based on Kullback–Leibler divergence (KLD), as follows:

$$JSD(P,Q) = \frac{1}{2}KLD(P,M) + \frac{1}{2}KLD(Q,M) \tag{17}$$

Where

$$M = \frac{1}{2}(P+Q) \tag{18}$$

$$KLD(P,Q) = \sum_{i} P(i)\ln\frac{P(i)}{Q(i)} \tag{19}$$

Jensen-Shannon divergence is bounded between 0 and $\ln(2)$. The square root of Jensen–Shannon divergence is referred to as Jensen-Shannon distance metric, which is used to quantify the distance between two probability distributions. In the present study, Jensen-Shannon distance metric was used to measure the distance between probability distributions of occupancy levels resulted from the different modeling scenarios.

3.3.8. Building performance indicators

To study the implications of the occupants' presence models for building performance simulation results, the author focused on four basic building-level (i.e. entire modeled area) performance indicators, namely annual heating and cooling demands per unit floor area [kWh.m^{-2}], and peak heating and cooling loads per unit floor area [W.m^{-2}]. 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 modeling a full HVAC system.

The simulations were conducted with 4 time steps per hour. Therefore, the heating and cooling energy required to maintain the temperature set-points in the office area could be obtained at 15-min intervals. Thus, the desired performance indicators were simply calculated by finding the annual sum and maximum value of the reported time-step heating and cooling energy demands and loads. The performance indicators were obtained for different modeling scenarios, whereby model 4 acts quasi as the "reality benchmark". Thereby, the implications of various occupants' presence models could be explored in view of the simulated values of building-level annual heating and cooling demands and peak loads.

3.4. Results

3.4.1. Short term predictions

Figure 7 to Figure 11 illustrate the cumulative distribution of the obtained values of the aforementioned statistics for the eight workplaces, namely prediction errors for AT, DT, and OD (absolute values in hours), SM, and NT (absolute values). A numeric summary of the results are provided in Table 10 and Table 11 to provide a general overview of occupancy prediction errors. Table 10 presents the 80th percentile of the errors. Table 11 shows the percentage of errors (expressed in terms of the five statistics) below five corresponding specific threshold values. These threshold values emerged from discussions within the aforementioned EU projects [48,49] pertaining to the implementation of predictive building systems control strategy and are intended to represent practically relevant minimum performance requirements that occupancy models (intended for deployment in the context of predictive building systems control) would need to meet. More specifically, eighty percent of predictions made by the models would be expected to lie below these threshold error values.

Note that these figures and tables entail the comparison of monitored and predicted values for all eight workplaces. The comparisons were performed for each workplace individually. However, the corresponding results closely agree in tendency with the combined results of all workplaces. Specifically, the relative performance of the three occupancy models studied did not display any noteworthy dependency on the type of the eight monitored workplaces (closed, semi-closed, open-plan). Hence, the results for individual workplaces are not included here.

Table 10. The 80th percentile of the errors for the three models

Evaluation statistics		Models		
	Unit	Reinhart	Page	MT
First Arrival time error (FA)	[hour]	1.2	1.4	1.0
Last Departure time error (LD)	[hour]	2.4	2.4	2.4
Occupancy Duration error (OD)	[hour]	2.3	2.2	1.6
Occupancy State Matching error (SM)	[-]	0.48	0.48	0.45
Number of Transitions error (NT)	[-]	3.3	3.6	2.9

Table 11. Percentage of predictions with errors below thresholds for five statistics

Evaluation statistics	Error threshold	Models		
		Reinhart	Page	MT
First Arrival time error (FA)	1.0 [hour]	74.2	70.0	78.5
Last Departure time error (LD)	1.0 [hour]	46.9	46.7	46.0
Occupancy Duration error (OD)	1.0 [hour]	45.3	46.1	58.1
Occupancy State Matching error (SM)	0.4 [-]	46.8	48.9	61.0
Number of Transitions error (NT)	2.0 [-]	61.5	56.8	63.5

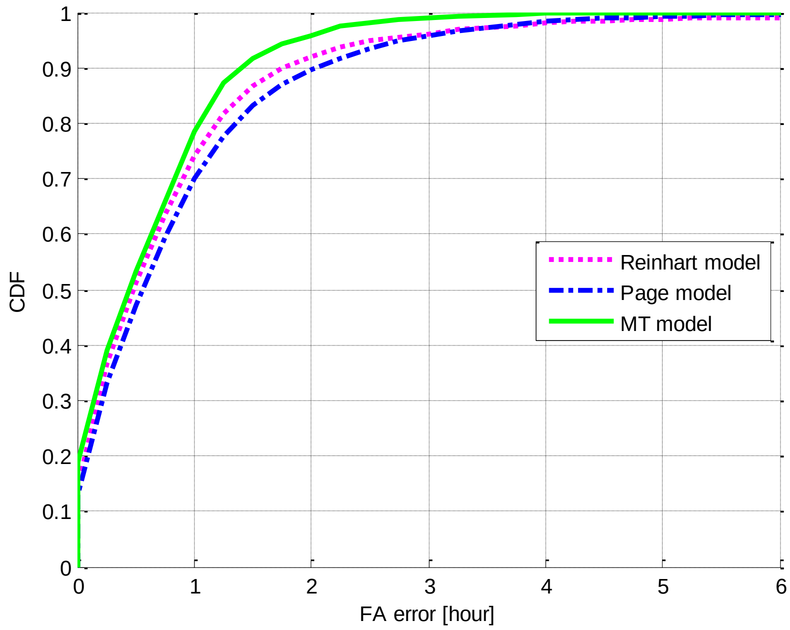

Figure 7. Cumulative distribution of first arrival time errors

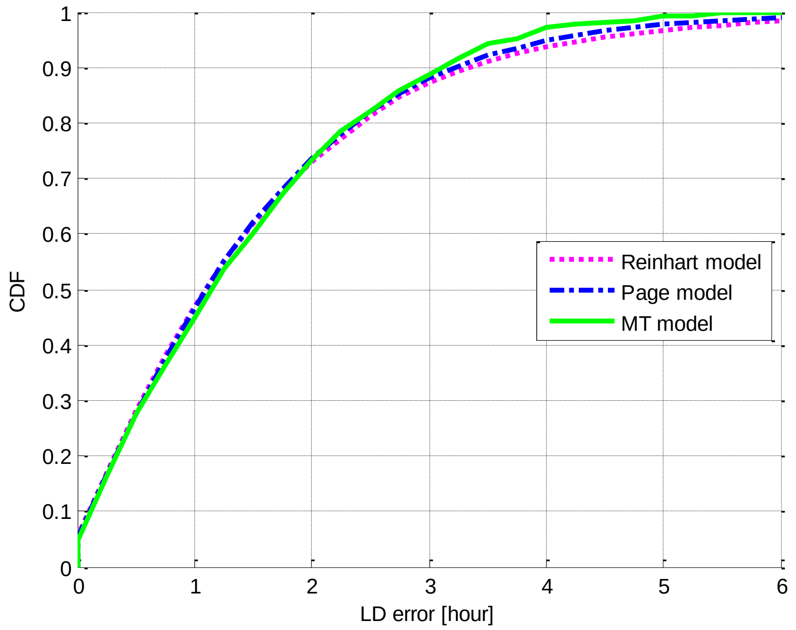

Figure 8. Cumulative distribution of last departure time errors

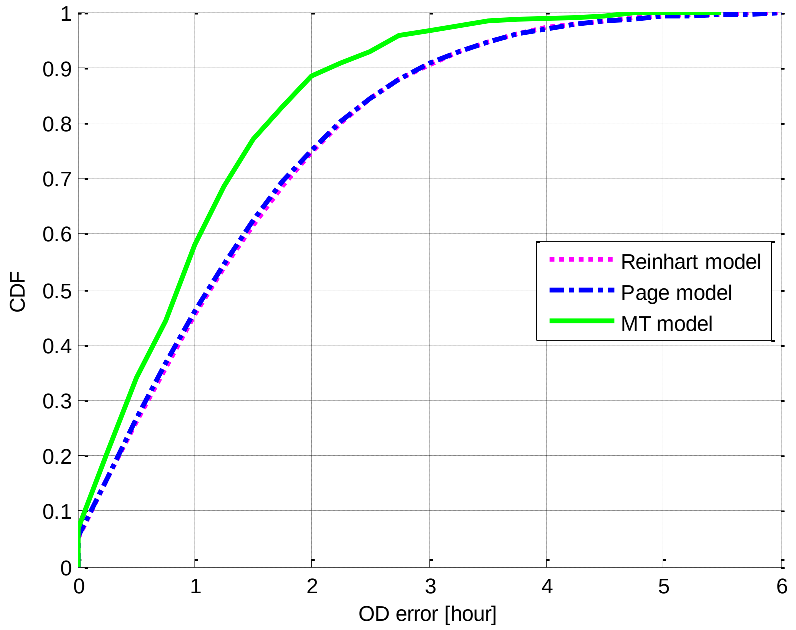

Figure 9. Cumulative distribution of occupancy duration errors

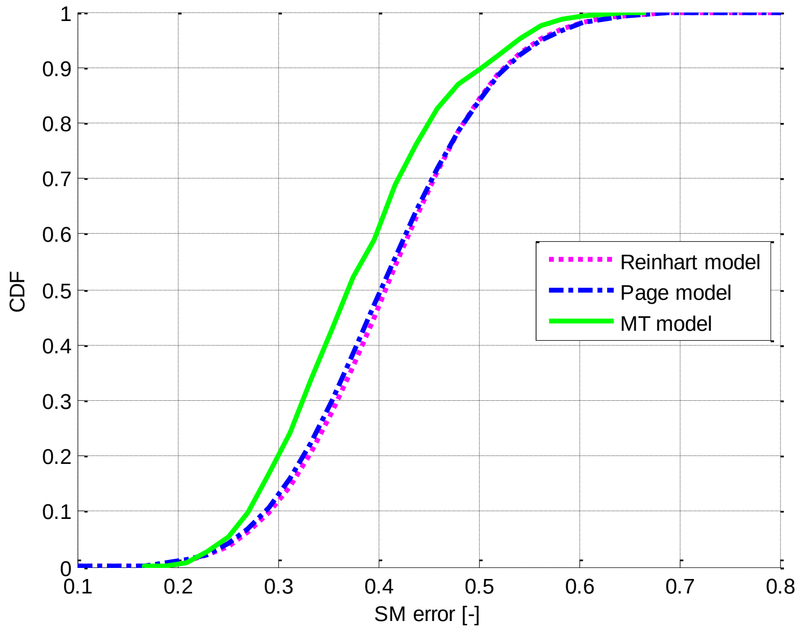

Figure 10. Cumulative distribution of occupancy state matching errors

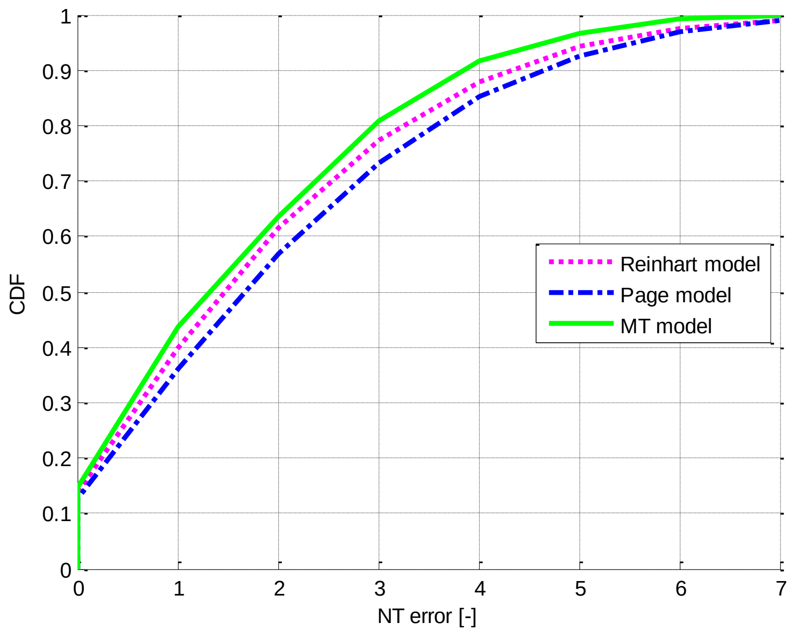

Figure 11. Cumulative distribution of number of transitions errors

3.4.2. Long term simulation

3.4.2.1. Comparison of modeling options in view of occupancy predictions

Figure 12 shows the cumulative probability distribution of occupancy levels in the modeled building throughout a year (expressed as the fraction of maximum occupancy) obtained from modeling scenarios 1a, 1b, 3a, 3b, and 4. Note that model 4, which is based on the original full-year occupancy data, acts as the reference.

Table 12 gives the Mean Error, RMSD, and Jensen-Shannon distance values, obtained via contrasting occupancy results of models 1a, 1b, 2a, 2b, 3a, and 3b with that of model 4, as the reference case. Table 13 provides the annual and peak values for internal heat gains (due to the occupant's presence and use of lights and electric equipment) obtained from different modeling scenarios. In addition, Table 14 gives the relative error of the obtained values for internal heat gains with reference to model 4 as benchmark.

3.4.2.2. Building performance Simulation results

The obtained values for annual heating and cooling demands and peak heating and cooling loads per conditioned floor area from the simulation models are provided in Table 13. As mentioned before, in case of models 1b, 2b, and 3b the stochastic occupancy model must be executed 365 times to obtain each occupant's random daily presence profiles for annual simulations. However, the random nature of daily occupancy patterns implies that slight differences could emerge, if the process would be repeated. Consequently, the obtained values of performance indicators could be also at least slightly different, if such annual simulations would be repeated multiple times. To address this concern, a full-fledged Monte Carlo model execution was conducted involving 100 runs for each model. Therefore, Table 13 includes, for models 1b, 2b, and 3b, both the mean values and the standard deviations resulting from the 100-run Monte Carlo analysis. In addition, Table 14 gives the relative errors of simulation results of models 1a to 3b, as well as models E and F, with reference to model 4 (considering the mean values from models 1b, 2b and 3b). Figure 13 and Figure 14 illustrate the cumulative distribution of heating and cooling load values for models E, 1a, 1b, 3a, 3b, 4, and F. Note that, as the results obtained from models 2a and 2b are very close to models 3a and 3b respectively, they have not been plotted in the figures, so that the data series can be better recognized.

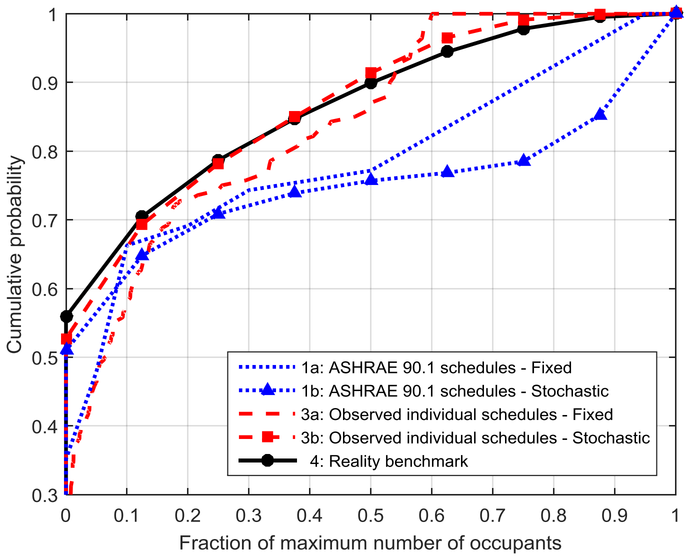

Figure 12. Cumulative distribution of occupancy levels obtained from different modeling scenarios

Table 12. Mean Error, RMSE, and Jensen-Shannon distance values for models 1a to 3b (compared with model 4)

Models	Mean error [%]	RMSE [%]	Square root of Jensen-Shannon divergence [-]
1a	11.7%	27.9%	0.36
1b	11.9%	29.5%	0.26
2a	0.0%	15.6%	0.19
2b	0.0%	20.7%	0.04
3a	0.0%	15.6%	0.19
3b	0.0%	19.9%	0.05

Table 13. Internal heat gains, heating and cooling demands per conditioned floor area obtained from simulations

Models	Annual internal heat gains [kWh/m^2]	Annual heating demand [kWh/m^2]	Annual cooling demand [kWh/m^2]	Peak internal heat gains [W/m^2]	Peak heating load [W/m^2]	Peak cooling load [W/m^2]
E	0.0	90.4	5.7	0.0	61.1	23.5
1a	51.9	65.9	18.5	17.2	49.4	39.4
1b	49.5 ± 0.03	67.0 ± 0.06	17.9 ± 0.05	18.7 ± 0.53	49.4 ± 0.61	39.6 ± 0.30
2a	22.3	79.9	9.7	7.0	58.5	30.0
2b	25.3 ± 0.03	78.2 ± 0.05	10.6 ± 0.03	11.7 ± 0.29	58.1 ± 0.43	31.8 ± 0.73
3a	23.1	79.5	9.9	7.1	58.6	30.2
3b	24.8 ± 0.14	78.4 ± 0.09	10.5 ± 0.06	13.9 ± 0.6	58.7 ± 0.36	32.0 ± 1.14
4	23.1	78.2	9.4	15.2	57.1	27.9
F	56.8	63.9	21.0	20.3	49.8	41.6

Table 14. Relative error of internal gains, heating and cooling demands with reference to model 4

Models	Relative error [%]					
	Annual internal heat gains	Annual heating demand	Annual cooling demand	Peak internal heat gains	Peak heating load	Peak cooling load
E	-100.0%	15.6%	-39.4%	-100.0%	7.0%	-15.8%
1a	124.7%	-15.7%	96.8%	13.2%	-13.5%	41.2%
1b	114.3%	-14.3%	90.4%	23.0%	-13.5%	41.9%
2a	-3.5%	2.2%	3.2%	-53.9%	2.5%	7.5%
2b	9.5%	0.0%	12.8%	-23.0%	1.8%	14.0%
3a	0.0%	1.7%	5.3%	-53.3%	2.6%	8.2%
3b	7.4%	0.3%	11.7%	-8.6%	2.8%	14.7%
F	145.9%	-18.3%	123.4%	33.6%	-12.8%	49.1%

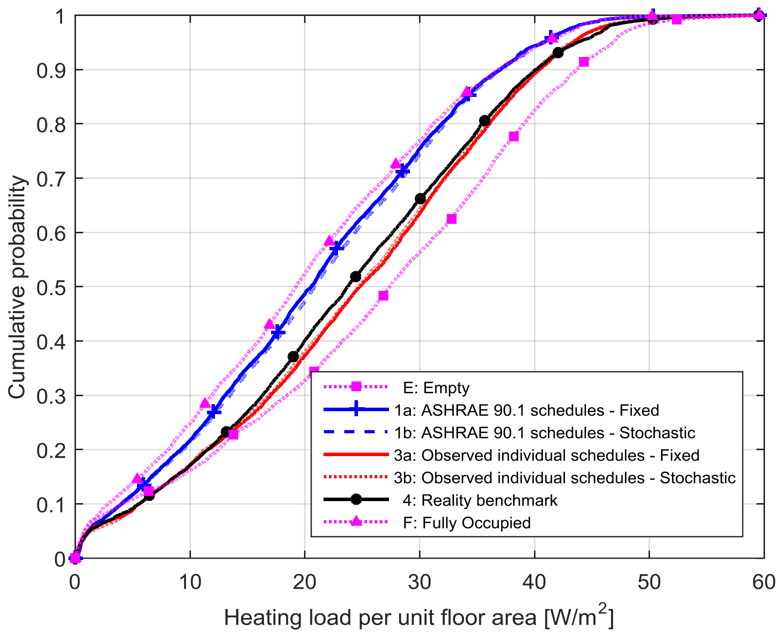

Figure 13. Cumulative distribution of simulated time-step heating loads

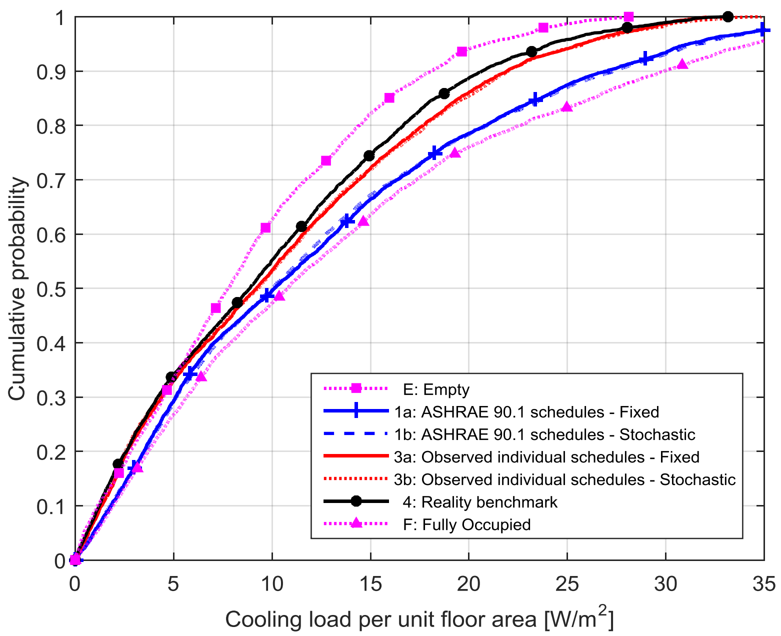

Figure 14. Cumulative distribution of simulated time-step cooling loads

3.5. Discussion

3.5.1. Short-term predictions

The results shown in Figure 7 to Figure 11, Table 10 and Table 11 facilitate a number of observations:

- With the exception of Last Departure (LD) errors, where all three models practically display the same performance, the simple non-probabilistic MT model performs best.
- The two probabilistic models generally display a comparable level of performance, even though Reinhart's model could be argued to perform slightly better with regard to the two indicators First Arrival time error (FA) and Number of Transitions error (NT).
- The expectation that at least eighty percent of model predictions would display errors below the aforementioned threshold error values is fulfilled by none of the models. The best performing non-probabilistic MT model comes close to meeting this requirement but only for one statistics (FA).

The author suggests that the presented results might have implications beyond the performance comparison of the three models considered:

- Firstly, it must be maintained that the obtained level of predictive accuracy was found to be rather low in general. Given the high quality and resolution of observational data used for model training in the present highly-controlled study, the more practical field applications of occupancy prediction models could be arguably expected to perform even poorer. It is important to emphasize that in the present study empirical data for each workplace (occupied by the same individual) was used to train the model for predicting the occupancy pattern at the very same workplace occupied by the very same individual. This circumstance could be reasonably argued to represent an ideal training scenario for occupancy models.

- Secondly, the study's results suggest that the models, which incorporate stochastic elements, do not necessarily display a superior predictive performance. Specifically, the two probabilistic models were outperformed in terms of their predictive potential by the proposed non-probabilistic model. The probabilistic models aim to reflect the random diversity in the occupancy patterns. This could be important in applications (such as the design and sizing of building systems) where the consideration of diversity is critical. However, in the case at hand (short-term occupancy prediction based on historical data), the non-probabilistic model remains close to the overall tendency of the past occupancy patterns, yielding thus a better predictive performance.

These remarks are not meant to suggest that the above mentioned issues represent conclusive evidence for generally existing limits to the predictive potential of occupancy models. For instance, it may be argued that the observed rather large model errors apply only to the present specific case study, which is limited, amongst other things, in terms of building type (office building) and number of workplaces (only eight). Likewise, the implemented probabilistic models are not necessarily representative of all that is currently available or could be developed in the future. Nonetheless, the obtained results do highlight the necessity for reflection on the achievable levels of accuracy in predicting future occupancy in buildings based on past data. The results of the present case study neither assert the full fidelity of occupancy models in predictive building systems control, nor do they confirm the contended effective pre-eminence of probabilistic occupancy modelling methods. Specifically, for applications involving building systems control, a probabilistic approach to represent the occupants' presence was not shown to enhance the accuracy of the integrated simulation models.

3.5.2. Long-term simulations

The obtained result leads to a number of noteworthy observations. Firstly, as illustrated in Figure 12 and considering the values for square root of Jensen-Shannon divergence in Table 12, the distribution of stochastic predictions of occupancy levels is closer to the actual occupancy level distribution. In addition, the observation-based stochastic models of occupants' presence (models 2b and 3b) provide peak values for internal heat gains much closer to the reality benchmark, compared to the ones with fixed profiles (models 2a and 3a). This, however, does not necessarily translate into a better predictive performance concerning indicators such as annual heating and cooling demands and peak heating and cooling loads (see Table 13).

Second and foremost, divergence of the simulation results of different models is not mainly due to the nature of occupants' presence models (i.e., stochastic versus non-stochastic). Options 1a and 1b yield fairly comparable results, as do options 2a and 2b, and options 3a and 3b. The significant difference is between generic (standard-based) assumptions (options 1a, 1b) and assumptions that rely on actual occupancy information (2a, 2b, 3a, 3b, 4). In the present case, standard-based assumptions (options 1a and 1b) obviously overestimate the actual occupancy (see Mean Error values in Table 12), resulting in systematically lower heating loads (see Figure 13) and systematically higher cooling loads (see Figure 14). These results are consistent in tendency with those of scenario F (full occupancy), which of course represents the ultimate overestimation of occupancy, thus resulting in the lowest and highest heating and cooling loads respectively.

The results of this case study suggest that randomization of occupants' presence patterns reduces the distance between the predicted and actual distributions of occupancy levels and provides more reliable peak values for occupancy loads. However, use of stochastic presence patterns per se does not guarantee that simulation results pertaining to typical building-level performance indicators (e.g., building annual and peak heating and cooling demands and loads) are any closer to reality than simulations based on non-probabilistic occupancy patterns. To achieve high-fidelity simulation results (at least with regard to building-level performance indicators such as heating and cooling annual demands and peak loads) it is thus much more important to possess reliable estimations of actual occupancy levels than whether probabilistic or non-probabilistic representations of presence patterns are deployed.

To clarify the scope of this part of the study, the author emphasizes that Chapter 3 focused on the implications of occupants' presence models (and not occupant behavior models) for simulation results. Nonetheless, in the current study the presence of occupants is not assumed to be totally irrelevant to equipment and lighting usage. However, the corresponding relationship is intentionally kept as simple as possible. Specifically, the modeling approaches examined in this study simply represent the occupants with a set of three schedules for presence, lighting, and equipment (either in a fixed or stochastic manner, either for an average person or for individuals). That is, they do not intend to model occupants as autonomous agents in the building and consequently, nor do they consider feedback loops from environmental conditions back to occupants' behavior. This circumstance is the logical consequence of this chapter's main objective to partially isolate the computable implications of occupants' presence patterns. In this context, one should not forget that representation of occupants with the above mentioned set of schedules is fairly common in the building performance simulation community. Therefore, this can be seen as an initial but important step towards assessing the sensitivity of building performance simulation results to the choice of different types of occupancy-related models.

As indicated before, the current work focused on occupants' presence and building-level performance indicators. Hence, the insights gained may not be directly applicable to simulation models involving behavioral factors and those with other levels of scale and zonal resolution. As such, it is likely that no single occupancy modeling approach can optimally accommodate all simulation deployment scenarios. Moreover, a thorough evaluation of occupancy-related models in terms of implications for building performance simulation results should ideally consider a multitude of simulation application scenarios (involving different building types, different zonal destinations, different phases of the building delivery process, different queries, etc.). This observation underscores the critical importance of further studies to explore and document the effectiveness level of various types of occupancy models within the multi-dimensional simulation deployment space.

Chapter 4.
Plug load models

4.1. Background

Office buildings' energy demand is significant. In Europe, total annual energy use of office buildings varies roughly from 100 to 1000 $kWh.m^{-2}.a^{-1}$, depending on factors pertaining to location, construction, environmental control systems, as well as equipment types and use patterns [56]. Generally speaking, office buildings' energy demand is due to both provision of proper indoor conditions (e.g., heating, cooling, ventilation, lighting) and operation of office equipment. The latter energy requirement is particularly affected by inhabitants' presence and behavior [57]. Plug loads play a significant role in office buildings, involving computers, peripheral devices, telephones, etc. A large fraction of office equipment is controlled by inhabitants [58]. Plug loads are suggested to account for more than 20% of primary energy used in office buildings, and this ratio is stipulated to increase by 40% in the next 20 years [59,60,61].

Reliable estimates of plug loads are important for adequate design decision making. Specifically, building performance simulation tools geared toward assessing buildings' energy and indoor environmental performance would benefit from reliable methods to estimate plug loads magnitude [62]. The current state of knowledge (including both available information in standards and typical simulation input assumptions) with regard to the prevailing plug loads in office buildings may be characterized as not fully satisfactory. Likewise, compared with other occupancy-relate models, there are arguably few studies regarding prediction methods of the magnitude and pattern of equipment use in office buildings. Given this circumstance, in Chapter 4 the plug load patterns of a number of inhabitants of a selected office are empirically explored. Thereby, both bulk (e.g., aggregated annual values) and detailed (i.e., time-dependent high resolution) electrical energy use patterns are considered, resulting in a simplified linear regression and a stochastic prediction method. Note that, given the small scope of the underlying empirical data, it is not claimed that the specific formulation of the proposed prediction methods is generally valid. Rather, the aim is to document the proposed approaches and illustrate their promising potential, which are to be further tested and refined via future – more extensive – cross-sectional investigations.

4.2. Methods

4.2.1. Overview

The main objective of this chapter is to explore the possibility of predicting plug loads of office buildings based on two sets of assumptions, namely the installed equipment power (specifically computers and peripherals) and the presence patterns of inhabitants. Put in general terms, it is hypothesized that plug loads or electrical energy use in an office building due to office equipment can be estimated based on installed equipment power and the presence patterns of office inhabitants. Specifically, two approaches are introduced in the present chapter. The first (simplified) approach aims at obtaining aggregate estimations such as annual plug loads in an office area or building given certain basic input data such as overall presence patterns and installed equipment power. The second (probabilistic) approach aims at emulating the stochastic nature of load fluctuations. Toward this end, high-resolution (empirically-based or stochastically generated) time series of office inhabitants are utilized. In the following, brief descriptions of the empirical setting and these two approaches are provided.

4.2.2. Monitored data

To provide both a concise illustration and an initial test of the proposed predictive approach toward estimation of office buildings' plug loads, an office area in a University building in Vienna, Austria was selected. The area includes both single-occupancy and open-plan office rooms/zones (see Table 15). The office area is used by eight regular staff members (referred to here as U1 to U8) of different backgrounds (Department director, secretarial assistant, academic assistants, research scientists). The office area is equipped with a comprehensive monitoring infrastructure. Of importance are, for the purposes of the present study, sensors for occupancy detection and plug loads monitoring. Specifically, plug loads associated with each inhabitant (computers, peripherals, telephones, etc.) are monitored on a regular basis. In this study, the primary analysis and the basis for model development are based on 15-minute interval data (inhabitants' presence, plug loads) collected over a one-year period (2014). To assess the developed models' reliability, two separate sets of empirical data from the years 2013 and 2015 were compiled. Note that the data included in this study concerning the installed power of desktop computers do not directly reflect their nameplate values. Rather, they have been derived based on nameplate information according to the insights gained in previous studies. These studies suggest that desktop computers consume on average 14 to 36% of the rated values [63,64]. In the present treatment, thus, a specific coefficient is defined, namely 0.3, which is to be applied to the nameplate values of desktop computers' power.

Table 15. Overview of the selected office zones with respective inhabitants, areas, and installed power (Q_e)

Space	Inhabitants	Total effective installed power [W]	Area [m^2]
Open-plan office area	U1, U2, U3, U4, U5	880	43
Single-occupancy office 1	U6	180	19
Single-occupancy office 2	U7	90	34
Single-occupancy office 3	U8	130	17

4.2.3. The simplified model

The author hypothesizes that the plug loads fraction is a function of presence probability. A linear version of this relationship could be represented as follows:

$$PLF_i = aPP_i + b \tag{20}$$

Where PLF_i is the plug loads fraction at time interval i, PP_i is the average presence probability at time interval i, and a and b are coefficients that would be empirically obtained.

Given these assumptions, the energy use associated with plug loads (PLE) over a time period consisting of n interval with a length of T can be estimated as follows:

$$PLE = T\sum_{i=1}^{n} PLF_i \times Q_e \tag{21}$$

Where Q_e is the effective power of the installed equipment at the office. Note that if individual presence and plug load profiles are available, this method can be used at the levels of individual office occupants as well. However, the model is intentionally simplified to rely on the average presence profile (for weekdays and weekends) which is commonly estimated for different building types in building performance simulation efforts.

For the office area investigated in the present study and using the empirical 2014 data, this relationship can be expressed via Equation 22. Figure 15 illustrates scatter plot of the 15-min presence probabilities and plug load fractions along with the fitted regression line.

$$PLF = 0.53PP + 0.09 \tag{22}$$

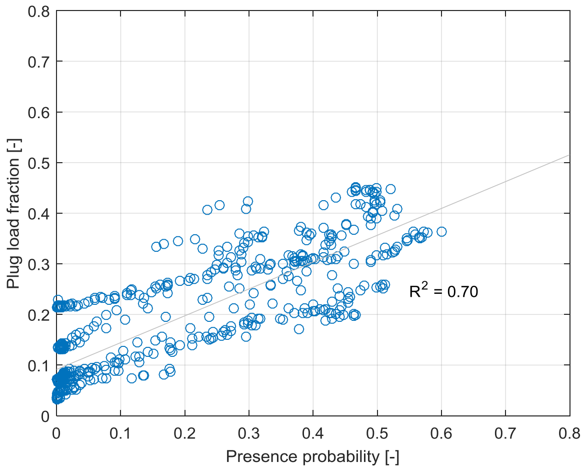

Figure 15. Linear regression analysis of the relationship between plug load fraction and presence probability for eight inhabitants

4.2.4. The stochastic model

To explore the potential of a probabilistic approach in predicting plug loads, a simple stochastic plug load model was formulated, which utilizes three specific Weibull distributions to characterize the following:

1. Plug load fractions during occupied periods or intermediate absences shorter than one hour;
2. Plug load fractions during intermediate absences longer than one hour;
3. Plug load fractions outside working hours.

Thereby, plug load fractions are picked randomly via inverse transform sampling method, whenever the occupancy state falls within one of the above possibilities. Consequently, similar to the aforementioned simplified model, the electrical energy use can be calculated via Equation 21.

The general formulation of a Weibull distribution is as follows, where *a* is the scale parameter and *b* is known as the shape parameter:

$$f(x|a,b) = \frac{b}{a}\left(\frac{x}{a}\right)^{b-1} e^{-\left(\frac{x}{a}\right)^{b}} \tag{23}$$

In order to obtain the parameters of the Weibull distributions, the monitored data pertaining to occupancy and plug loads at the studied office area in year 2014 was used in the maximum likelihood estimation method (see Table 16). Figure 16 illustrates cumulative distribution function of the Weibull distributions for the aforementioned cases.

Whereas the empirical distribution functions could be used to establish the stochastic model for the purpose of current study, the fitted Weibull distributions were deployed, so that the model can be used (and further tested by other researchers) without fully depending on high resolution monitoring data on occupancy and equipment use.

Table 16. Parameters of stochastic plug load model's Weibull distributions (obtained from observations in the selected office area for the year 2014)

Model's Weibull distributions	a (scale)	b (shape)
1	0.560	1.886
2	0.377	1.323
3	0.141	1.072

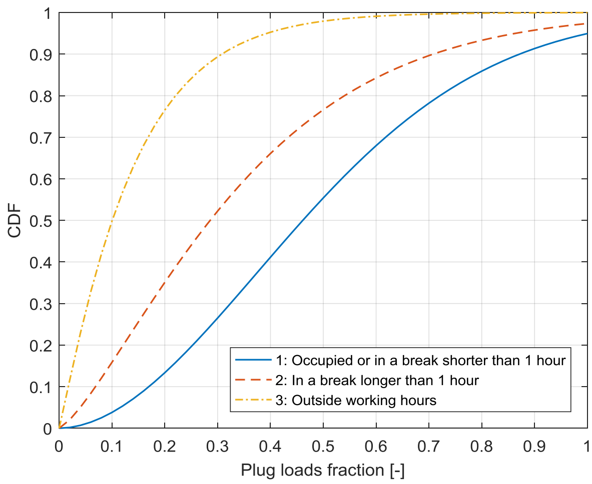

Figure 16. Cumulative distribution function of the stochastic plug load model's Weibull distributions

However, it should be noted that to use this model the occupancy states (occupied or vacant) of individuals at each time interval should be provided as input. In this regard two scenarios were considered: A) Use of high-resolution monitored data for the whole running period, and B) using a stochastic occupancy model to generate non-repeating daily occupancy profiles based on limited information about occupancy patterns. While the first scenario represents a sort of ideal situation to depict the model's potential, the second scenario offers a more practical option: A number of stochastic occupancy models have been emerged, which can use relatively simple input information (i.e., observation-based or standard-based diversity profiles). For the purpose of current study, the stochastic occupancy model developed by Page et al. [44] was used. This model uses as input a profile of presence probability and average parameter of mobility (μ), which is defined as the ratio of state change probability to state persistence probability. Similar to the implementation of the linear regression model, the stochastic model was provided with average presence profiles for weekdays and weekends. Note that the model itself does not include default values for the – potentially highly influential – mobility factor. To explore the implications for the method's predictive performance, two values for mobility factor were considered, namely 0.5 and 0.1, leading to scenarios B1 and B2 respectively. Table 3 summarizes the implementation scenarios of the stochastic plug load model.

Table 17. Implementation scenarios of the stochastic plug load model

Scenario	Input data	Coupled occupancy model
A	Individuals' monitored occupancy data	-
B1	Average monitored presence profiles for weekdays and weekends	Stochastic model [44] with μ = 0.5
B2	Average monitored presence profiles for weekdays and weekends	Stochastic model [44] with μ = 0.1

4.3. Results and discussion

4.3.1. The simplified model performance

Table 18 provides a summary of the monitored and calculated total and peak electrical energy use (due to office equipment) in the selected areas for the years 2014, 2013, and 2015, together with the predictions' relative errors with reference to the measurements. In addition, to compare the distribution of predicted and monitored plug loads, the Jensen–Shannon divergence metric was utilized (Equations 17 to 19).

Table 18 also includes the values of three statistical indicators, namely Root Mean Square error (RMSE), Normalized Root Mean Square Error (NRMSE), and Mean Bias Error (MBE) for interval by interval comparison of the monitored and calculated energy use.

From the results, it can be inferred that, for the selected case study building, the proposed method can provide good predictions of the annual electrical energy use for office equipment. Interestingly, the proposed method's "predictive" performance was better for the years 2013 and 2015, even though it was developed based on the 2014 data. However, with regard to the peak plug loads and the distribution of time interval predictions, the model yields relatively large errors, as it relies on average reference-day presence and plug load profiles.

4.3.2. The stochastic model performance

As shown in Table 19, the stochastic method's performance in predicting annual, peak, and time interval plug loads was evaluated in the same manner. However, in case of the stochastic model, the values provided in Table 19 are mean values of a 100-run Monte Carlo simulation of the model. In addition, as explained before, the stochastic plug load model was implemented in 3 different scenarios in terms of input occupancy data (Table 17).

Table 18. Comparison of simplified plug load model's predictions with monitored electrical energy use associated with plug loads for the years 2013 to 2015

Model	Run period	Run period sum		Run period peak		Distribution	Time interval values		
		Value [kWh]	RE [%]	Value [W]	RE [%]	JSD [-]	MBE [W]	RMSE [W]	NRMSE [%]
Measured	2014	2289.7	-	1190.9	-	-	-	-	-
Simplified model	2014	1960.4	-14.4	510.3	-57.2	0.44	-37.6	162.8	14.4
Measured	2013	1978.0	-	1157.8	-	-	-	-	-
Simplified model	2013	1958.1	-1.0	513.5	-55.6	0.51	-2.3	129.3	12.0
Measured	2015	1801.5	-	1058.4	-	-	-	-	-
Simplified model	2015	1863.1	3.4	503.6	-52.4	0.42	7.0	138.1	13.7

The obtained results suggest that the implemented stochastic method for office plug loads does not provide very accurate predictions of the annual electrical energy use. However, it provides fairly good estimations of peak loads.

Considering different implementation scenarios of the stochastic plug load model, it can be seen that the selection of input parameters for the stochastic occupancy model (in this study the parameter of mobility), has a large impact on the resulting energy use predictions. Specifically, for the office area studied here, setting the parameter of mobility to 0.5 results in a large overestimation of annual plug loads. However, when using a parameter of mobility of 0.1, model predictions converge to those obtained via high resolution occupancy data input.

Table 19. Comparison of stochastic plug load model's predictions with monitored electrical energy use associated with plug loads for the years 2013 to 2015

Model	Run period	Run period sum		Run period peak		Distribution	Time interval values		
		Value [kWh]	RE [%]	JSD [-]	RE [%]	JSD [-]	MBE [W]	RMSE [W]	NRMSE [%]
Measured	2014	2289.7	-	1190.9	-	-	-	-	-
Stochastic model, Scenario B1	2014	2904.5	26.9	1092.3	-8.3	0.34	70.2	199.4	17.6
Stochastic model, Scenario B2	2014	2388.1	4.3	1018.1	-14.5	0.35	11.2	182.7	16.2
Stochastic model, Scenario A	2014	2424.3	5.9	1033.5	-13.2	0.33	15.4	141.5	12.5
Measured	2013	1978.0	-	1157.8	-	-	-	-	-
Stochastic model, Scenario B1	2013	2835.6	43.4	1098.6	-5.1	0.37	97.9	209.4	19.4
Stochastic model, Scenario B2	2013	2354.8	19.1	1007.5	-13.0	0.38	43.0	181.7	16.9
Stochastic model, Scenario A	2013	2374.3	20.0	1057.8	-8.6	0.36	45.3	123.2	11.4
Measured	2015	1801.5	-	1058.4	-	-	-	-	-
Stochastic model, Scenario B1	2015	2782.7	54.5	1091.9	3.2	0.34	112.0	205.0	20.3
Stochastic model, Scenario B2	2015	2333.5	29.5	1004.1	-5.1	0.34	60.8	175.2	17.3
Stochastic model, Scenario A	2015	2322.7	28.9	1009.8	-4.6	0.33	59.5	137.3	13.6

4.3.3. Comparative performance of the models

The comparison of model predictions with observed data facilitates a number of conclusions. The simplified method provides fairly reasonable predictions of annual energy use associated with plug loads. Indeed, the performance of the simplified model was in this regard considerably better than the more sophisticated probabilistic model implementations in the validation years 2013 and 2015 (see Figure 17). However, the probabilistic plug load model, independent of the variations implemented, outperforms the simplified model in terms of peak load (see Figure 18) and the distribution of predictions. The latter can be inferred from the lower values of JSD (see Table 18 and Table 19) and is clearly illustrated for year 2013 in Figure 19. With regard to the time interval plug loads, comparing the models with the same level of input (the simplified model versus the probabilistic model in implementation scenarios B1 and B2), reveals a better performance on the side of the simplified model.

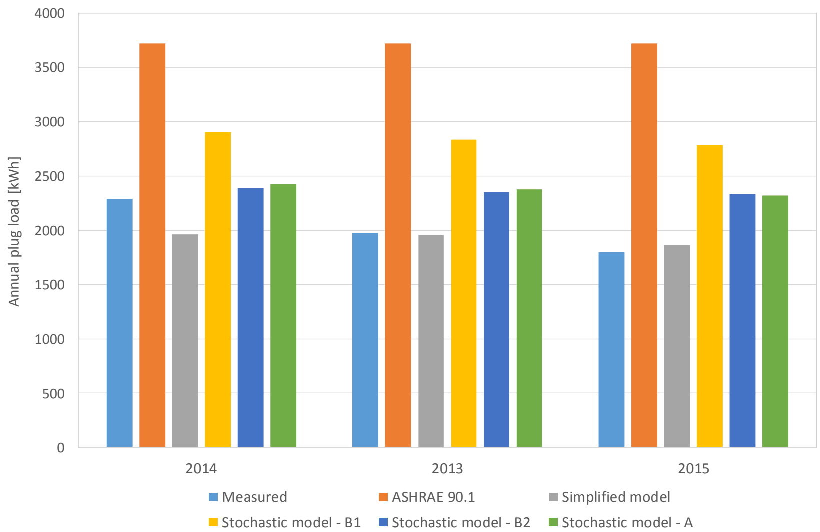

Figure 17. Annual plug load obtained from different modelling approaches, along with the respective monitored values

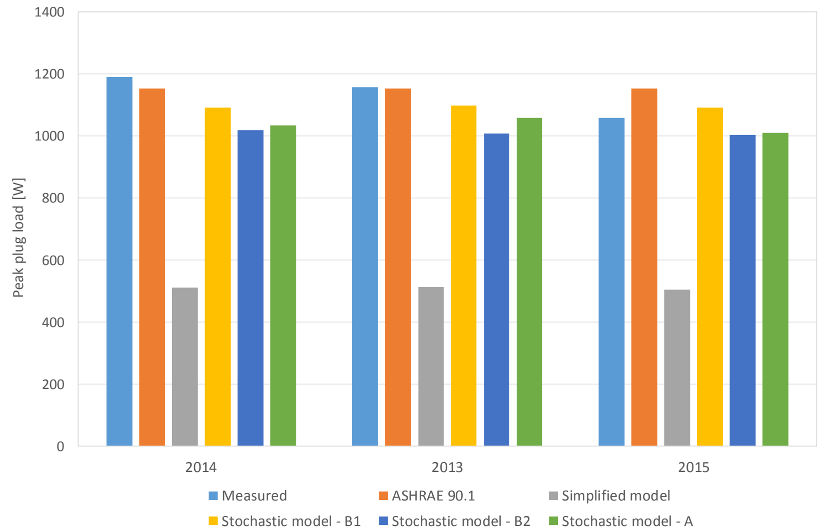

Figure 18. Peak plug load obtained from different modelling approaches, along with the respective monitored values

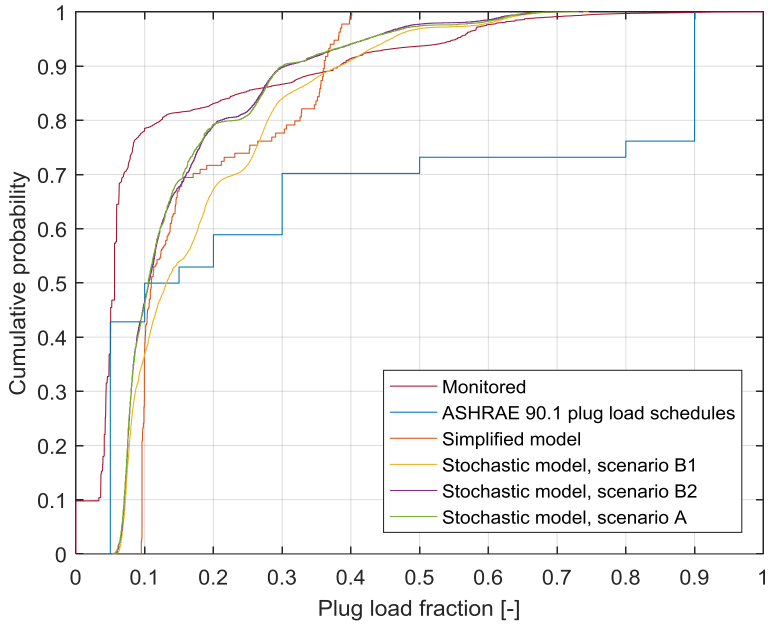

Figure 19. Cumulative distribution of plug load fraction obtained from different modelling scenarios for year 2013, along with the respective monitored values

Chapter 5.
Window operation models

5.1. Background

Given the impact of inhabitants' presence and control actions on indoor environment, building performance simulation tools increasingly incorporate models of occupants' presence and behavior to assess, among other things, building energy performance 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.

Since more than a decade ago, 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 [65,66,67,68,69]. 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 [70,71,72]. However, 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 [11], and on the other side, the lack of robust algorithms for use of these models in building performance simulation [8]. In addition, as outlined in previous publications [12,14], arguably, the relationship between the purpose of building performance simulation-based studies and the choice of occupancy-related models is not sufficiently recognized.

Given this background, in the current dissertation the author conducts 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, an office area was selected, for which long-term data on outdoor and indoor environment, occupancy, and window operation is available. As deployed in previous studies [73,74], 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, the author takes 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, the implications of different window operation models for simulation-based assessments of building heating energy demand and occupants' thermal comfort could be also studied.

Thus, the study allows for exploration of 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?

5.2. Methods

5.2.1. 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.

5.2.2. 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, the focus was specifically 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 20 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, 15-minute interval data from a calendar year (referred to as calibration period) was used 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.

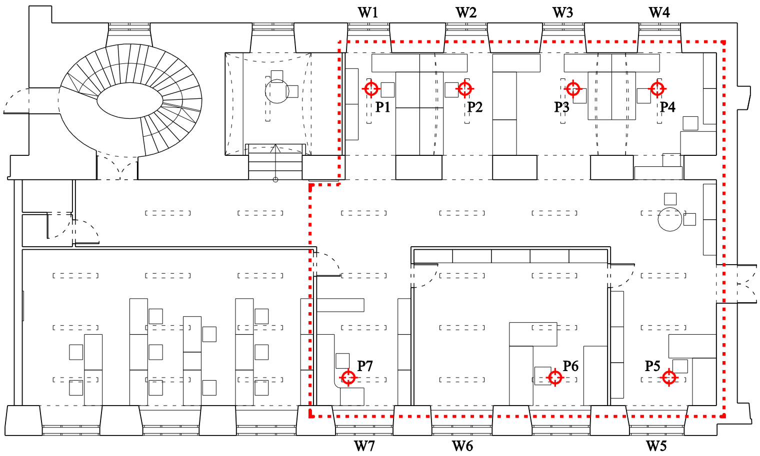

Figure 20. Schematic illustration of the office area, observed occupants (P1-P7) and operable windows (W1-W7).

5.2.3. Selected window operation models

Three existing stochastic and three simple non-stochastic window operation models were studied. 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 20 provides a list of independent variables considered in the models. To the author's 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 the current study, new variations of models A and C (denoted as A* and C*) were also included, 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, two benchmark pseudo-models (denoted as G and H) were considered, 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. [66], 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 [67], 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 [68], 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 20).
- 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 all the models are implemented such that the opening and closing actions on each window are triggered only if the occupant associated with that window is present (see Figure 20, which illustrates the arrangement of monitored occupants and the operable windows assigned to them).

Table 20. 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
			Ground floor	0.820 ± 0.140	NA
	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

5.2.4. 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 [29], the airflows across the external windows and the connected spaces were simulated. Figure 20 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 [75]. 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 21 summarizes basic information about the office area energy model.

In the present study, the building calibrated simulation model is used as a test bed for evaluation of window operation models, which allows for considering the models feedback, i.e. the impact of models' output (window states) on models' input (indoor temperature). The calibrated building model also makes it possible to determine the impact of window operation (and use of different window operation models) on the simulated building performance indicators. To fulfill these purposes, a model was needed that could represent the building performance in validation period with high accuracy. Therefore, the monitored data pertaining to occupancy, plug loads, use of lights, and operation of heating system were incorporated 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, the author relied on the 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 [76] 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. A benchmark model was also built, 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, the heating and free-running periods was set 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, two approaches were adopted for the different model evaluation purposes. In one variation of the building model, which was 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 [75]). 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, an ideal non-limited heating system was defined, which maintains the indoor temperature of different zones according to the measured indoor temperatures in the validation period. This approach makes it possible 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 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 21. 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
Exterior windows SHGC [-]	0.77
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}

5.2.5. Evaluation scenarios for window operation predictions

Two approaches were adopted 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 predicted window operations on indoor environmental inputs.

In the first approach, which has been adopted in previous studies [73, 74], 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, the author suggests 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, the performance of window operation models to predict the inhabitants' interactions with windows are evaluated 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, both original and adjusted coefficients of the logit functions were used. 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. The models with original coefficients are specified 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 20 lists the stochastic models' independent variables, and the original and adjusted estimates of their coefficients.

5.2.6. Evaluation statistics for window operation predictions

For the purpose of the current study, the following indicators were used 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 [68,73,74] to evaluate the predictive performance of window operation models. Three indictors were added 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.

5.2.7. Building performance indicators

To study the implications of using different window operation models for building performance simulation results in a systematic manner, different building performance indicators were considered 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, 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 were obtained. These variations allow for better analysis of the performance of window operation models in comparison with the benchmark model.

Concerning the free-running season, the minimum, average and maximum value of free-floating indoor temperatures were obtained. In addition, the occupants' thermal comfort based on EN15251 adaptive thermal comfort model was assessed. More specifically, as building performance indicators, 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 were calculated (Category III, with an acceptable range of comfort temperature $\pm$ 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.

5.2.8. Implementation of window operation models

For the evaluation of window operation models without considering the models' feedback, the models were implemented 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. The models were implemented with complete set of input parameters published by the modelers. 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, the models were implemented within the building simulation model using the EnergyPlus runtime language. For the implementation of the models in EnergyPlus the author benefited from a study by Gunay et al. [8] 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 this 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, the author needed to rewrite the codes to a large extent for the purpose of this study.

It is worthwhile to mention that, the authors in [8] have tried to resolve some of the shortcomings in the models, whereas in the current study it was 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 aforementioned study 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 the author's 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 this case, the monitored presence data was pre-processed using 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.

5.3. Results and discussion

5.3.1. Model evaluation approaches

The obtained values of evaluation indicators for different window operation models are given in Table 22 (without considering the models' feedback) and Table 23 (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). In case of stochastic models, the results are obtained via a 50-run Monte-Carlo simulation of window operation models (In all following tables, a single-value output from the stochastic models represents mean value of the multiple model executions. When a range of values is provided, it denotes the mean and standard deviation of the outcomes).

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, the evaluation was conducted using two alternatives, namely with and without inclusion of models' feedback. Given the respective results shown in Table 22 and Table 23, 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.

Table 22. Evaluation statistics without inclusion of models' 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 23. Evaluation statistics with inclusion of models' 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

5.3.2. Window operation predictions

To better illustrate the performance of models in terms of different evaluation indicators, Figure 21, Figure 22, and Figure 23 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.

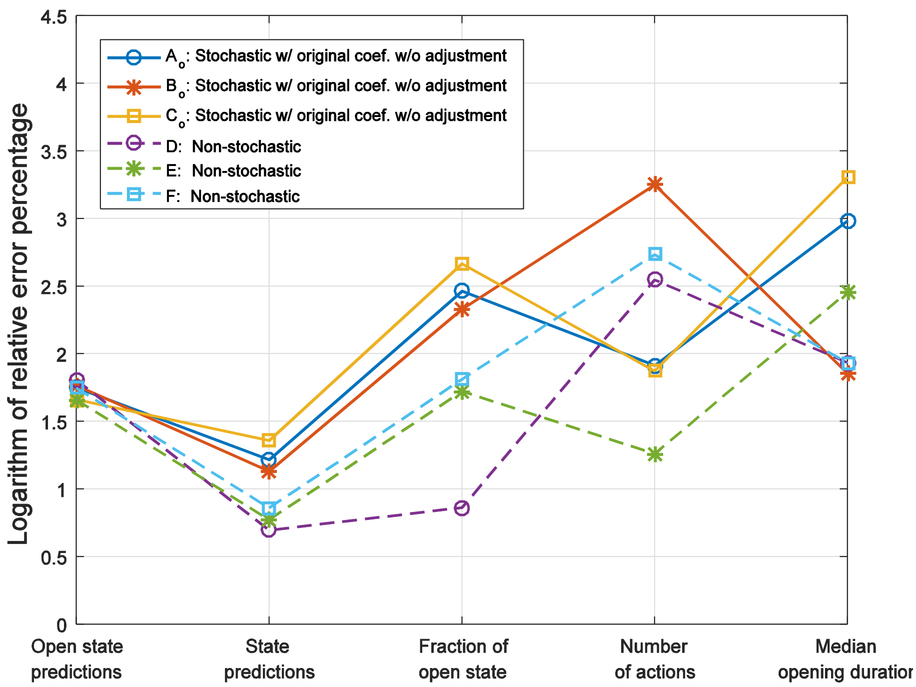

Figure 21. Errors of stochastic window operation models with original coefficients and no adjustment as well as non-stochastic models in terms of 5 evaluation statistics

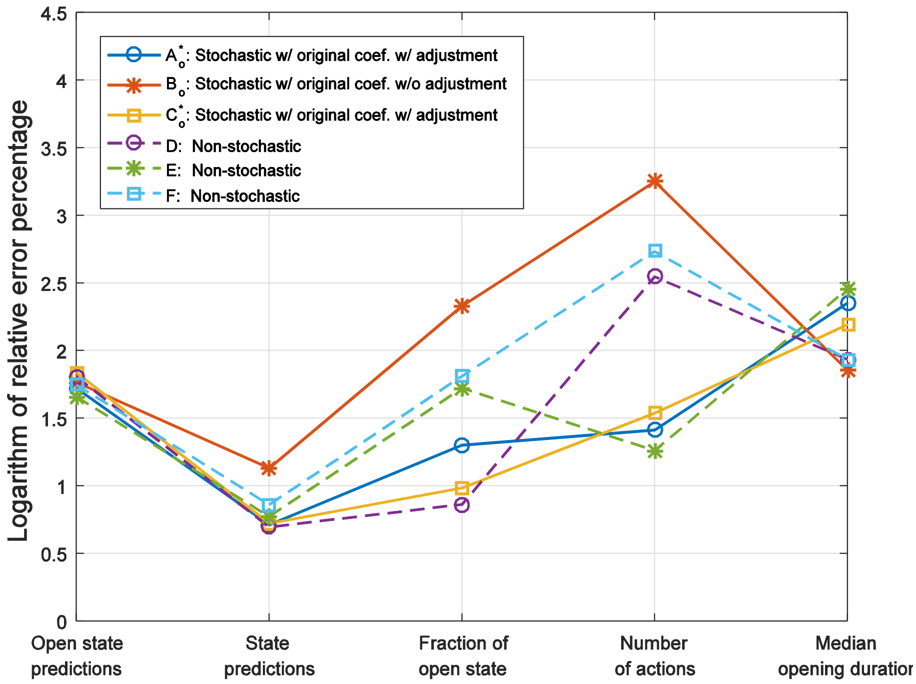

Figure 22. Errors of stochastic window operation models with original coefficients and adjusted to buildings without night time ventilation as well as non-stochastic models in terms of 5 evaluation statistics

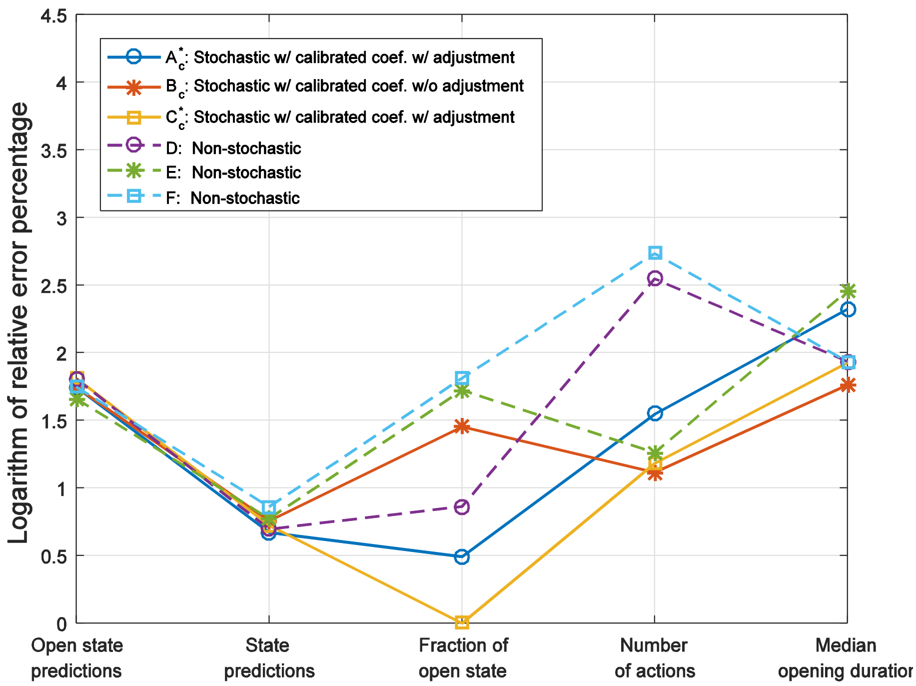

Figure 23. Errors of stochastic window operation models with calibrated coefficients and adjusted to buildings without night time ventilation as well as non-stochastic models in terms of 5 evaluation statistics

A fundamental question with regard to the application of behavioral models concerns their capability in reproducing empirical observations. Thus, it may be first asked 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, it can be concluded that without adjustments (night-time ventilation, calibrated coefficients), none of the studied models performs satisfactorily (see Table 22 and Table 23 as well as Figure 21). 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 instead of the conventional no-feedback assumption (see Table 22), a more realistic simulation-based test with feedback inclusion is conducted (see Table 23). However, the nighttime ventilation adjustment markedly improves the performance of the stochastic models A_o* and C_o* (see Figure 22). 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 23).

More specifically, concerning the models’ performance in heating and free-running seasons, Figure 24, Figure 25 and the results provided in Table 24 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. Even considering models A* and C* (as models indented to be used for this season and adjusted to the building under study in terms of night time ventilation) the overestimation of opening duration in heating season is considerable (see Figure 24).

- 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). As a result, 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' behavioral 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. As shown in Figure 25, non-stochastic models without a dead-band (models D and F) largely overestimate the number of actions. Model E performs noticeably better in terms of the number of actions, but overestimates the fraction of open state and median opening duration.

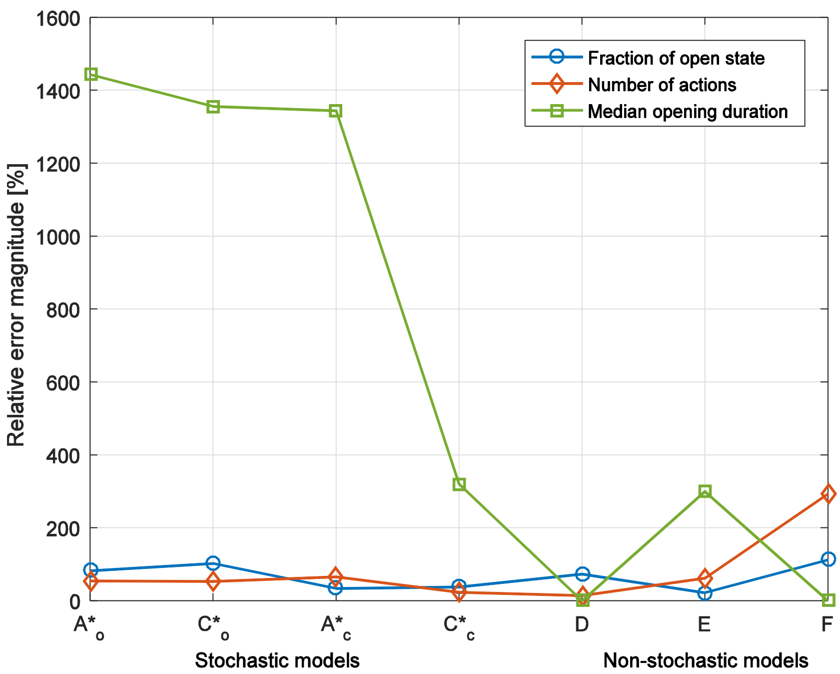

Figure 24. The magnitude of relative error in fraction of open state, number of actions, and median opening duration in the heating season

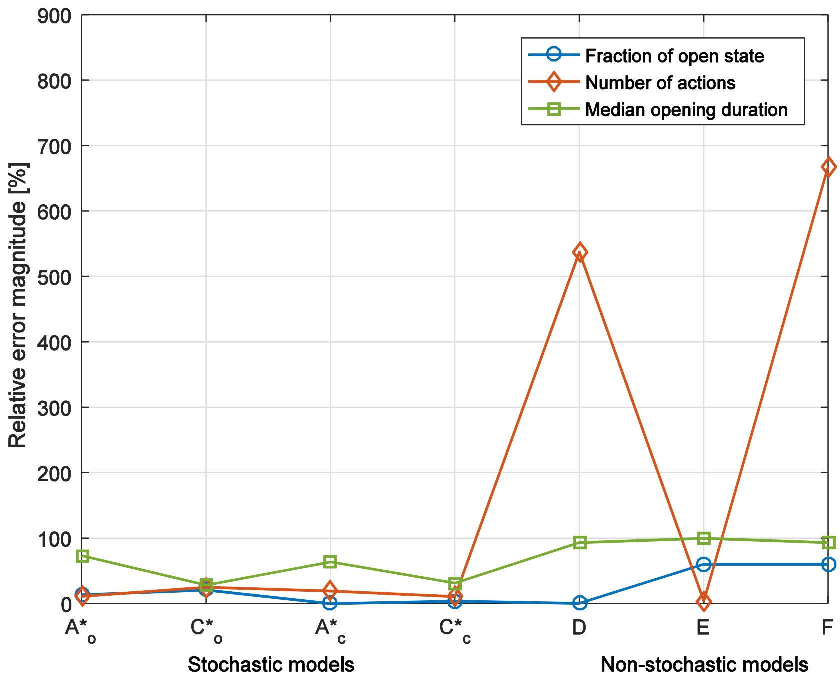

Figure 25. The magnitude of relative error in fraction of open state, number of actions, and median opening duration in the free-running season

Table 24. 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]
Benchmar	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

5.3.3. Annual heating demand predictions

As shown in Table 25, 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 24). 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. Figure 26 illustrates the annual heating demands obtained from models A*, C*, D, and E in comparison with the benchmark value.

Table 25. Obtained values for building heating demand indicators

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

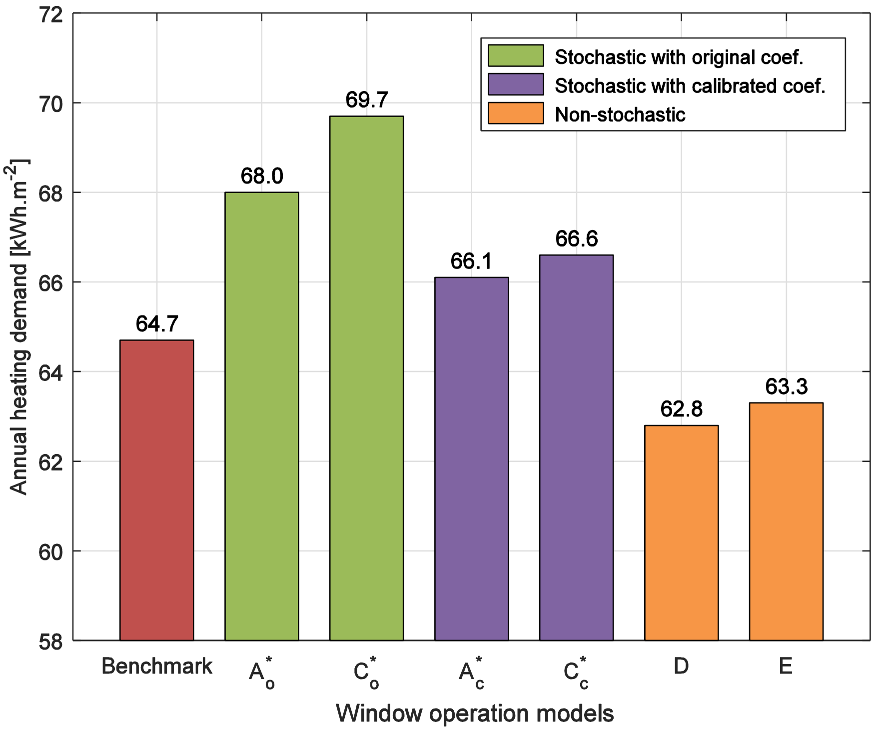

Figure 26. The annual heating demands obtained from adjusted stochastic models with original and calibrated coefficients, along with the non-stochastic ones in comparison with benchmark model

5.3.4. Peak heating demand predictions

The peak heating demand in one year may not be the most appropriate benchmark to analyze 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. The 99.6th percentile of heating demands was also provided to make the benchmark less affected by single events.

Considering the 15-min and hourly-integrated peak heating demand values provided in Table 25, 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. This is also illustrated in Figure 27 and Figure 28, which only include the stochastic models adjusted to the building under study. 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 26 shows the number of open windows, the office area air change rate, and the outdoor temperature at the time of peak. As it can be seen from the results provided in Table 26, the stochastic models overestimate the number of coincident open windows in cold conditions. Concurrent opening of 4 out of 7 windows in an 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. Besides, to benefit from the of stochastic models' potential in generating more realistic distributions and peak values of occupancy-related parameters, stochastic weather data inputs should be also deployed. With deployment of the common typical year weather data for building performance simulation, there is no guarantee that the realistic peak values predicted by the occupancy-related models translate into accurate (or absolute) peak heating (or cooling) demands.

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.

Table 26. Number of open windows at peak heating demand , along with air change rate and outdoor temperature

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

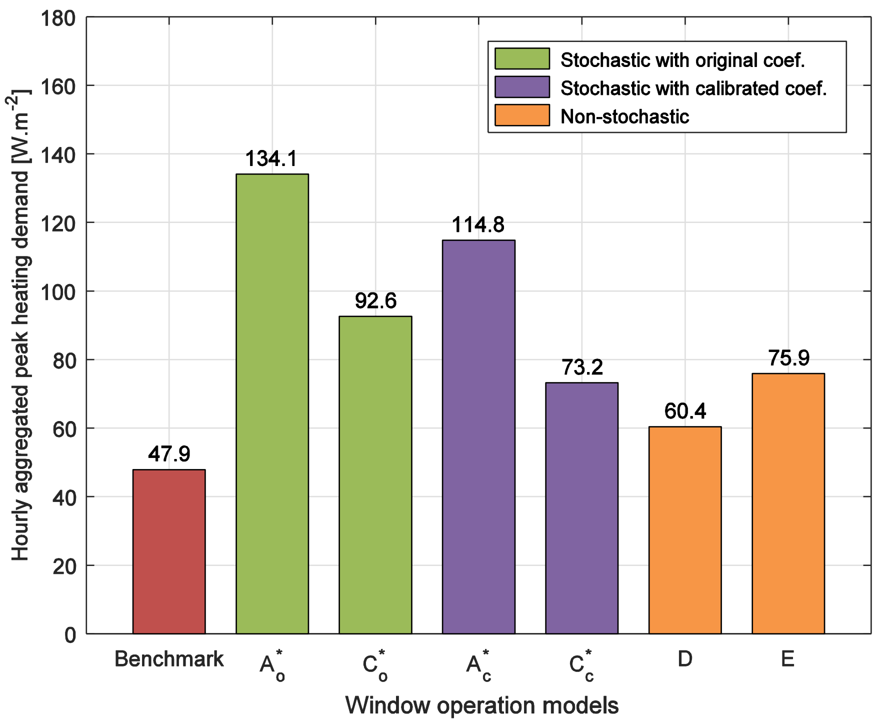

Figure 27. Hourly aggregated heating demands obtained from adjusted stochastic models with original and calibrated coefficients, along with the non-stochastic ones in comparison with benchmark model

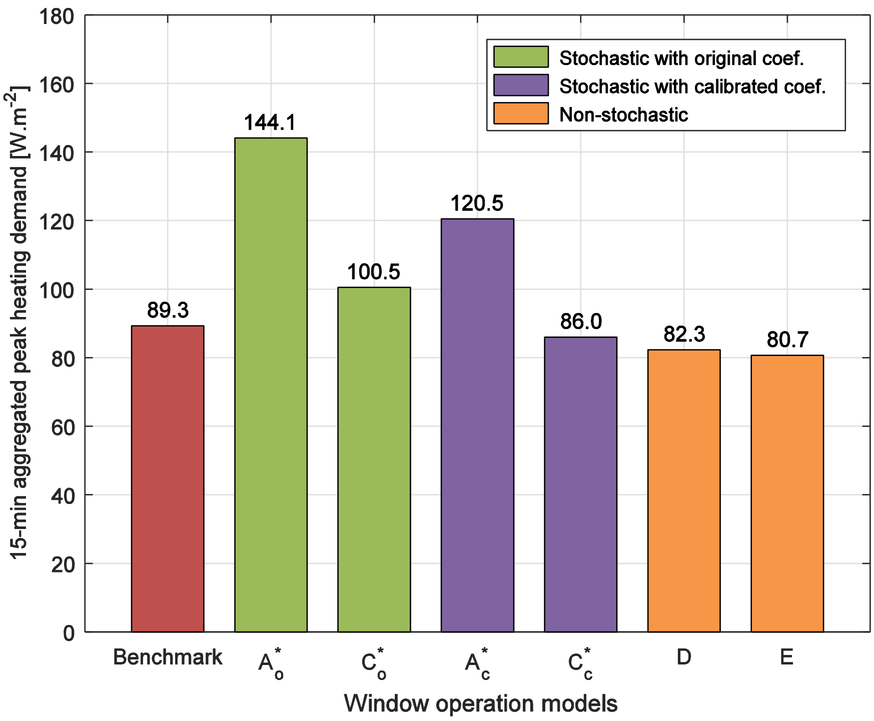

Figure 28. The 15-min aggregated heating demands obtained from adjusted stochastic models with original and calibrated coefficients, along with the non-stochastic ones in comparison with benchmark model

5.3.5. Free-running season assessments

According to Table 27, 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 29). However, as shown in Figure 30, 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.

Table 27. Obtained values for free-running building performance indicators

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

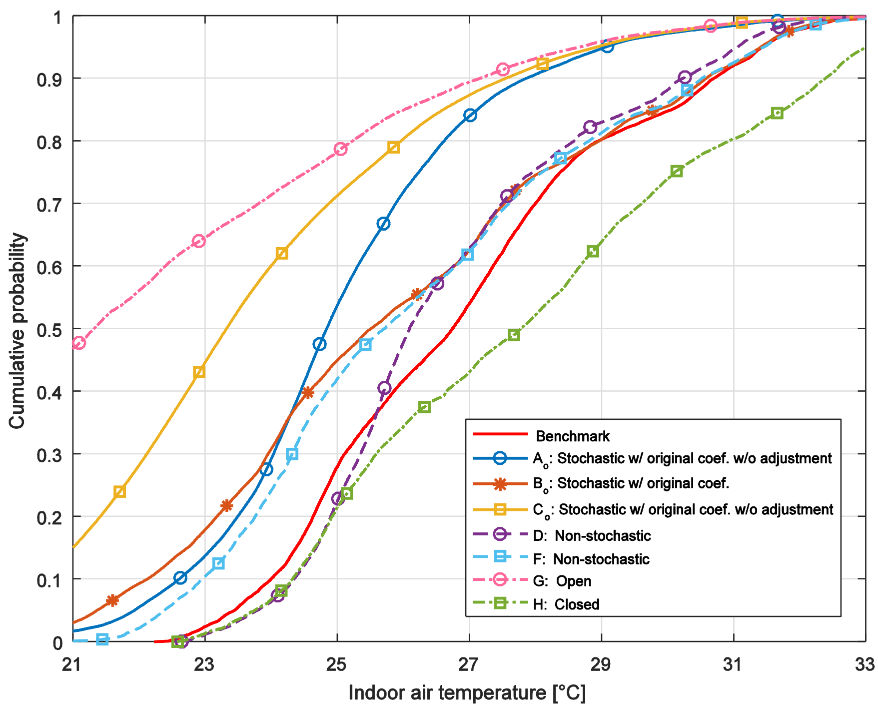

Figure 29. Cumulative distribution of free-floating temperatures obtained from stochastic models A_o, B_o, and C_o, non-stochastic models D and F, as well as benchmark and pseudo-models G and H.

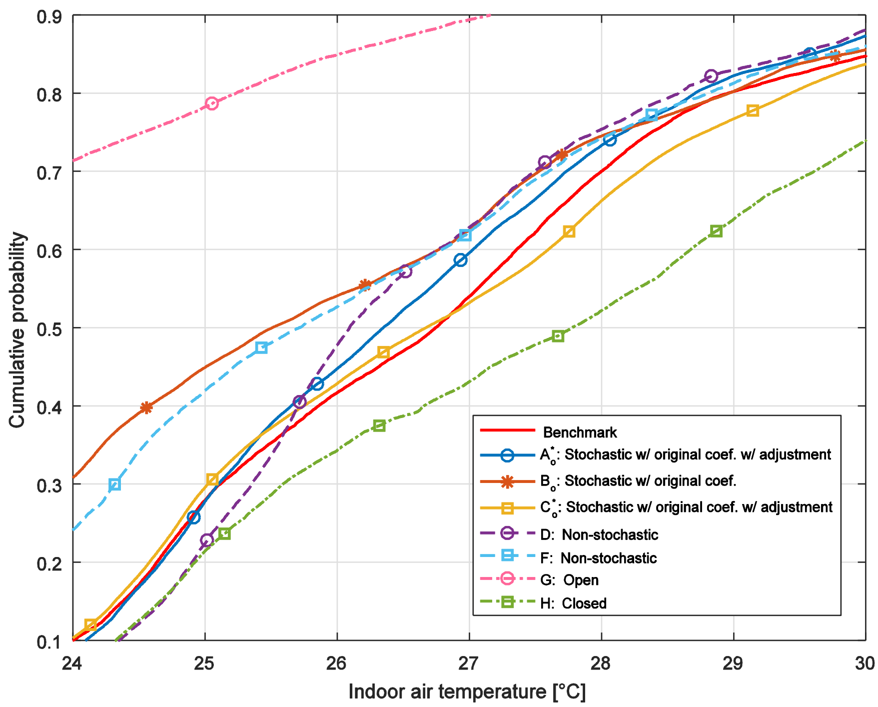

Figure 30. Cumulative distribution of free-floating temperatures obtained from stochastic models A_o*, B_o, and C_o*, non-stochastic models D and F, as well as benchmark and pseudo-models G and H.

Chapter 6.
Conclusion

6.1. Contributions

As noted at the outset of this dissertation, deployment of occupancy models in building performance simulation requires a rigorous standard concerning the evaluation of the models' predictive performance. To address this issue, the author suggested an evaluation approach of occupant presence models. Thereby, the building simulation models deployment scenarios were considered in formulation of the evaluation workflow and metrics. In this context, from the author’s view, an evaluative approach similar to the one applied in this dissertation – albeit on a larger scale – would be critical for future studies that intend to evaluate and improve the predictive potential of occupancy models.

Moreover, to explore the implications of different presence models for a number of standard building performance simulation results, the annual heating and cooling demands and peak heating and cooling loads of an office area were computed using a dynamic energy simulation tool. Thereby, conventional standard-based diversity profiles, observational average and individual occupancy-related schedules, random realizations of these profiles, and the year-long observational data on occupancy, lighting, and equipment use were deployed to represent occupants’ presence in the simulation model. The results suggest that stochastic models can provide a better representation of occupants’ presence in terms of distribution and peak values. However, this does not mean that they are necessarily more reliable in simulating building-level energy performance indicators. Moreover, the discrepancy in the results of different modeling approaches is not primarily due to the probabilistic versus non-probabilistic nature of the occupants’ presence models.

Rather, the key difference is between generic (standard-based) assumptions and those that rely on actual occupancy information.

With regard to the plug loads, the study points to a potentially useful relationship between inhabitants' presence, their respective installed equipment power, and the resulting electrical energy use. Using this relationship, a simplified non-stochastic and a stochastic method for the prediction of electrical energy use in buildings due to office equipment operation were proposed and tested.

In addition, a number of stochastic and non-stochastic window operation models were also studied 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, the author could not infer superior performance of these models for heating demand assessments, as they could not capture the occupants’ behavior 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.

6.2. Future research

In author’s 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 occupant presence and behavior models in different deployment scenarios as well as development of more generally applicable occupancy-related models.

Moreover, as stressed before, the present study was based on a limited set of empirical data obtained from one office area. Ongoing and future – more extensive – cross-sectional investigations in this area are expected to utilize a larger empirical foundation and thus lead to more representative and inclusive development and evaluation of occupant behavior models that could be embedded in high resolution building performance modeling and energy simulation applications.

6.3. Publications

As of this writing, various portions and reports on earlier stages of this work have been published in the following articles:

An inquiry into the reliability of window operation models in building performance simulation
F Tahmasebi, A Mahdavi
Building and Environment 105 (2016), 343-357

The sensitivity of building performance simulation results to the choice of occupants’ presence models: a case study
F Tahmasebi, A Mahdavi, Journal of Building Performance Simulation (2015)
DOI: 10.1080/19401493.2015.1117528

Predicting people's presence in buildings: An empirically based model performance analysis
A Mahdavi, F Tahmasebi
Energy and Buildings 86 (2015), 349-355

The deployment-dependence of occupancy-related models in building performance simulation
A Mahdavi, F Tahmasebi
Energy and Buildings 117 (2016), 313-320

Prediction of plug loads in office buildings: simplified and probabilistic methods

A Mahdavi, F Tahmasebi, M. Kayalar
Energy and Buildings 129 (2016), 322-329

Exploring the Implications of Different Occupancy Modelling Approaches for Building Performance Simulation Results

F Tahmasebi, S Mostofi, A Mahdavi
Energy Procedia 78 (2015), 567–572

A systematic assessment of the sensitivity of building performance simulation results with regard to Occupancy-related input assumptions

F Tahmasebi, A Mahdavi
Proceedings of the 14th International Conference of IBPSA, 1397-1403, 2015

A two-staged simulation model calibration approach to virtual sensors for building performance data

F Tahmasebi, A Mahdavi
Proceedings of the 13th International Conference of IBPSA, 25-28, 2013

Exploring the predictive potential of probabilistic occupancy models

F Tahmasebi, A Mahdavi
Proceedings of the 5th German-Austrian IBPSA Conference, 48-52, 2014

Simulation model calibration: an optimization-based approach

F Tahmasebi, R Zach, M Schuss, A Mahdavi
Proceedings of the 4th German-Austrian IBPSA Conference, 386-391, 2012

Optimization-based simulation model calibration using sensitivity analysis

F Tahmasebi, A Mahdavi
7th Conference of IBPSA-CZ, Brno, Czech Republic, 2012

Chapter 7.
References

7.1. Literature

[1] A. Mahdavi, Computational building models: theme and four variations, Proceedings of building simulation '03, Eindhoven, vol. 1, 2003, pp. 3-17.

[2] J.A. Clarke, J.L.M. Hensen, Integrated building performance simulation: Progress, prospects and requirements, Building and Environment 91 (2015) 294 - 306.

[3] A. Mahdavi, People in building performance simulation, in Building Performance Simulation for Design and Operation, edited by J. Hensen, R. Lamberts, 56-83. New York: Taylor & Francis, 2011, ISBN: 9780415474146.

[4] K. Schakib-Ekbatan, F.Z. Çakıcı, M. Schweiker, A. Wagner, Does the occupant behavior match the energy concept of the building? – Analysis of a German naturally ventilated office building, Building and Environment 84 (2015), 142-150, doi: 10.1016/j.buildenv.2014.10.018.

[5] H.B. Gunay, W. O'Brien, I. Beausoleil-Morrison, A critical review of observation studies, modeling, and simulation of adaptive occupant behaviors in offices, Building and Environment, Volume 70, December 2013, Pages 31–47, doi:10.1016/j.buildenv.2013.07.020.

[6] S. D'Oca, T. Hong, A data-mining approach to discover patterns of window opening and closing behavior in offices, Building and Environment 82 (2014), 726-739, doi:10.1016/j.buildenv.2014.10.021.

[7] T. Hong, S. D'Oca, W.J.N. Turner, S.C. Taylor-Lange, An ontology to represent energy-related occupant behavior in buildings. Part I: Introduction to the DNAs framework, Building and Environment, Volume 92, October 2015, Pages 764–777, doi:10.1016/j.buildenv.2015.02.019.

[8] H.B. Gunay, W. O'Brien, I. Beausoleil-Morrison, Implementation and comparison of existing occupant behavior models in EnergyPlus, Journal of Building Performance Simulation (2015), DOI: 10.1080/19401493.2015.1102969.

[9] A. Mahdavi, Common fallacies in representation of occupants in building performance simulation, Proceedings of Building Simulation Applications 2015 - 2nd IBPSA-Italy Conference, pp. 1-7, Bozen-Bolzano University Press, ISBN: 978-88-6046-074-5.

[10] D. Yan, W. O’Brien, T. Hong, X. Feng, H.B. Gunay, F. Tahmasebi, A. Mahdavi, Occupant behavior modeling for building performance simulation: current state and future challenges, Energy and Buildings 107 (2015) 264-278, doi:10.1016/j.enbuild.2015.08.032.

[11] W. Parys, D. Saelens, H. Hens, Coupling of Dynamic Building Simulation with Stochastic Modelling of Occupant Behavior in Offices – A Review-Based Integrated Methodology, Journal of Building Performance Simulation 4 (4): 339–358. doi: 10.1080/19401493.2010.524711.

[12] A. Mahdavi, F. Tahmasebi, The deployment-dependence of occupancy-related models in building performance simulation, Energy and Buildings 117 (2016) 313–320, doi:10.1016/j.enbuild.2015.09.065.

[13] F. Tahmasebi, A. Mahdavi, The sensitivity of building performance simulation results to the choice of occupants' presence models: a case study, Journal of Building Performance Simulation (2015), doi:10.1080/19401493.2015.1117528.

[14] I. Gaetani, P. Hoes, J.L.M. Hensen, Occupant behavior in building energy simulation: Towards a fit-for-purpose modeling strategy, Energy and Buildings 121 (2016) 188–204, doi:10.1016/j.enbuild.2016.03.038.

[15] A. Mahdavi, Simulation-based control of building systems operation, Building and Environment, Volume 36, Issue 6, July 2001, pp. 789–796.

[16] J. Cipriano, G. Mor, D. Chemisana, D. Pérez, G. Gamboa, X. Cipriano, Evaluation of a multi-stage guided search approach for the calibration of building energy simulation models, Energy and Buildings, Volume 87, 1 January 2015, pp. 370–385, doi:10.1016/j.enbuild.2014.08.052.

[17] G. Mustafaraj, D. Marini, A. Costa, M. Keane, Model calibration for building energy efficiency simulation, Applied Energy, Volume 130, October 2014, pp. 72–85, doi:10.1016/j.apenergy.2014.05.019.

[18] M. Giuliani, G.P. Henze, A.R. Florita, Modelling and calibration of a high-mass historic building for reducing the rebound effect in energy assessment, Energy and Buildings, Volume 116, 15 March 2016, pp. 434–448, doi:10.1016/j.enbuild.2016.01.034.

[19] H.W. Samuelson, A. Ghorayshi & C.F. Reinhart, Analysis of a simplified calibration procedure for 18 design-phase building energy models, Journal of Building Performance Simulation, Volume 9, 2016, Issue 1, pp 17-29, doi: 10.1080/19401493.2014.988752.

[20] G. Georgiou, M. Eftekhari, P. Eames, Calibration and validation of residential buildings: 8 case studies of detached houses, Proceedings of 2nd IBPSA–England Conference on Building Simulation and Optimization, London, UK. 2014.

[21] F. Tahmasebi, A. Mahdavi, Monitoring-based optimization-assisted calibration of the thermal performance model of an office building, Proceedings of 1st International Conference on Architecture & Urban Design, Tirana, Albania, April 2012, pp. 1111–1116.

[22] T. Reddy, I. Maor, C. Panjapornpon, Calibrating detailed building energy simulation programs with measured data - Part I: General methodology, HVAC&R RESEARCH 13-2. DOI:10.1080/10789669.2007.10390952.

[23] T. Reddy, I. Maor, C. Panjapornpon, Calibrating detailed building energy simulation programs with measured data - Part II: Application to three case study office buildings, HVAC&R RESEARCH 13-2. DOI:10.1080/10789669.2007.10390953.

[24] P. Raftery, M. Keane, J. O'Donnell, Calibrating whole building energy models: An evidence-based methodology, Energy and Buildings, 43 (2011), pp. 2356–2364.

[25] P. Raftery, M. Keane, A. Costa, Calibrating whole building energy models: detailed case study using hourly measured data, Energy Build, 43 (2011), pp. 3666–3679.

[26] Z. Yanga, B. Becerik-Gerberb, A model calibration framework for simultaneous multi-level building energy simulation, Applied Energy, Volume 149, July 2015, pp. 415–431, doi:10.1016/j.apenergy.2015.03.048.

[27] Y. Ji, P. Xu, A bottom-up and procedural calibration method for building energy simulation models based on hourly electricity submetering data, Energy, Volume 93, Part 2, December 2015, pp. 2337–2350, doi:10.1016/j.energy.2015.10.109.

[28] EnergyPlus, http://apps1.eere.energy.gov/buildings/energyplus/.

[29] L. Gu, Airflow Network Modelling in EnergyPlus, 10th International Building Performance Simulation Association Conference, Beijing, China, 2007.

[30] Matlab, http://www.mathworks.com/products/matlab/.

[31] LBNL, GenOpt user manual, Lawrence Berkeley National Laboratory, Available at: http://SimulationResearch.lbl.gov.

[32] B. Coffey, A development and testing framework for simulation-based supervisory control with application to optimal zone temperature ramping demand response using a modified genetic algorithm, M.Sc. thesis, Concordia University, 2008.

[33] A. Saltelli, M. Ratto, T. Andres, Global Sensitivity Analysis - The Primer. John Wiley & Sons Inc., 2011, ISBN: 978-0-470-05997-5.

[34] B. Polly, N. Kruis, D. Roberts, Assessing and improving the accuracy of energy analysis for residential buildings, U.S. National Renewable Energy Laboratory's (NREL), Sponsoring organization: U.S. Department of Energy, 2011, report number: DOE/GO-102011-3243.

[35] DOE 2011. EnergyPlus application guide for EMS (a.k.a. The book of EnergyPlus runtime language). US Department of Energy.

[36] E. Azar, C.C. Menassa, A comprehensive analysis of the impact of occupancy parameters in energy simulation of office buildings, Energy and Buildings 55 (2012) 841–853.

[37] Z. Yang, B. Becerik-Gerber, The coupled effects of personalized occupancy profile based HVAC schedules and room reassignment on building energy use, Energy and Buildings 78 (2014) 113–122.

[38] ASHRAE 90.1-2013: Energy Standard for Buildings Except Low-Rise Residential Buildings, American Society of Heating, Refrigerating and Air-Conditioning Engineers, Inc., Atlanta, 2013.

[39] J.A. Davis III, D.W. Nutter, Occupancy diversity factors for common university building types, Energy and Buildings 42 (2010) 1543–1551.

[40] C. Duarte, K.V.D. Wymelenberg, C. Rieger, Revealing occupancy patterns in an office building through the use of occupancy sensor data, Energy and Buildings 67 (2013) 587–595.

[41] G.R. Newsham, A. Mahdavi, I. Beausoleil-Morrison, Lightswitch: a stochastic model for predicting office lighting energy consumption, in: Proceedings of Right Light Three, the 3rd European Conference on Energy Efficient Lighting, Newcastle, UK, 1995, pp. 59-66.

[42] C.F. Reinhart, Daylight availability and manual lighting control in office buildings simulation studies and analysis of measurements, Ph.D. thesis, Technical University of Karlsruhe, Germany, 2001.

[43] D. Wang, C.C. Federspiel, F. Rubinstein, Modeling occupancy in single person offices, Energy and Buildings 37 (2005) 121–126.

[44] J. Page, D. Robinson, N. Morel, J.-L. Scartezzini, A generalized stochastic model for the simulation of occupant presence, Energy and Buildings 40 (2008), 83–98.

[45] I. Richardson, M. Thomson, D. Infield, A high-resolution domestic building occupancy model for energy demand simulations, Energy and Buildings 40 (2008) 1560–1566.

[46] C. Liao, Y. Lin, P. Barooah, Agent-based and graphical modelling of building occupancy, Journal of Building Performance Simulation 5(1), 2010, pp. 5–25.

[47] C.E. García, D.M. Prett, M. Morari, Model predictive control: Theory and practice – A survey, Automatica, Volume 25, Issue 3, May 1989, pp. 335–348.

[48] CAMPUS 21 project: Control and Automation Management of Buildings and Public Spaces. <http://www.campus21-project.eu> (accessed 27.07.14).

[49] RESSEEPE project: REtrofitting Solutions and Services for the enhancement of Energy Efficiency in Public Edification. <http://www.resseepe-project.eu> (accessed 27.07.14).

[50] R. Zach, S. Glawischnig. M. Hönisch, R. Appel, A. Mahdavi, MOST: An open-source, vendor and technology independent toolkit for building monitoring, data pre-processing, and visualization, in: G. Gudnason, R. Scherer (Eds.), eWork and eBusiness in Architecture, Engineering and Construction, Taylor & Francis, Reykjavik, 2012, pp. 97–103.

[51] C.F. Reinhart, Lightswitch-2002: A model for manual and automated control of electric lighting and blinds, Solar Energy 77 (2004), 15–28.

[52] F. Tahmasebi, M. Schuss, A. Mahdavi, Monitoring-based dynamically updated occupancy models for predictive building systems control, in: Proceedings of 10th Nordic Symposium on Building Physics, Lund, Sweden, 2014, pp. 550–557.

[53] F. Tahmasebi, A. Mahdavi, Generation and evaluation of embedded probabilistic occupancy models for predictive building systems control, in: Proceedings of 10th European Conference on Product & Process Modelling, Vienna, Austria, 2014.

[54] DOE, EnergyPlus Energy Simulation Software: Weather Data, apps1.eere.energy.gov/buildings/energyplus/cfm/weather_data.cfm (accessed 30.06.2016).

[55] ASHRAE 90.1-2013 User's Manual, American Society of Heating, Refrigerating and Air-Conditioning Engineers, Inc., Atlanta, 2013.

[56] D. Caccaveli, H. Gugerli, TOBUS – A EU diagnosis and decision making tool for office building upgrading, Energy and Buildings, 34, 2002, pp. 113–119.

[57] Z. Wang, Y. Ding, Occupant-based energy consumption prediction model for office equipment, Energy and Buildings, 109, 2015, pp. 12–22

[58] K. Mc Kenney, M. Guernsey, R. Ponoum, J. Rosenfeld, Commercial miscellaneous electric loads: energy consumption characterization and savings potential in 2008 by building type, Technical report D498, DOE, Building Technologies Program, 2010.

[59] Buildings energy data book, Office of Energy Efficiency and Renewable Energy, U.S. Department of Energy, 2011.

[60] K. Roth, K. Mc Kenney, C. Paetsch, R. Ponoum, US residential miscellaneous electric loads electricity consumption, In: ACEEE study on energy efficiency in buildings, 2008.

[61] G. Ghatikar, H.I. Cheung, S. Lanzisera, Miscellaneous and electronic loads energy efficiency opportunities for commercial buildings: a collaborative study by the United States and India, Lawrence Berkeley National Laboratory and Infosys Technologies Limited, 2013.

[62] H.B. Gunay, W. O'Brien, I. Beausoleil-Morrison, S. Gilani, Modeling plug-in equipment load patterns in private office spaces, Energy and Buildings 121 (2016) 234–249, doi:10.1016/j.enbuild.2016.03.001.

[63] M.H. HOSNI, Test method for measuring radiant/convective split of heat gains from equipment in buildings, ASHRAE Research Project, 822, 1997.

[64] B.W. JONES, Measurement of heat gain and radiant convective split from equipment in buildings, ASHRAE Research Project, 1055, 1997.

[65] S. Herkel, U. Knapp, J. Pfafferott, Towards a model of user behavior regarding the manual control of windows in office buildings, Building and Environment 43 (2008) 588–600. doi:10.1016/j.buildenv.2006.06.031.

[66] H.B. Rijal, P. Tuohy, M.A. Humphreys, J.F. Nicol, A. Samuel, J. Clarke, Using results from field surveys to predict the effect of open windows on thermal comfort and energy use in buildings, Energy and Buildings 39 (2007), pp. 823-836, doi:10.1016/j.enbuild.2007.02.003.

[67] G.U. Yun, K. Steemers, Time-dependent occupant behavior models of window control in summer, Building and Environment 43 (2008), pp 1471-1482, doi:10.1016/j.buildenv.2007.08.001.

[68] F. Haldi, D. Robinson, Interactions with window openings by office occupants, Building and Environment 44 (2009), pp 2378-2395, doi: 10.1016/j.buildenv.2009.03.025.

[69] R.K. Andersen, V. Fabi, J. Toftum, S.P. Corgnati, B.W. Olesen, Window opening behavior modelled from measurements in Danish dwellings, Building and Environment 69 (2013), pp 101-113. doi: 10.1016/j.buildenv.2013.07.005.

[70] F. Haldi, D. Robinson, The impact of occupants' behavior on building energy demand, Journal of Building Performance Simulation, 4:4, pp. 323-338, DOI: 10.1080/19401493.2011.558213.

[71] S. D'Oca, V. Fabi, S.P. Corgnati, R.K. Andersen, Effect of thermostat and window opening occupant behavior models on energy use in homes, BUILD SIMUL (2014) 7: 683–694, DOI 10.1007/s12273-014-0191-6.

[72] S.T. Moghadam, F. Soncini, V. Fabi, S. Corgnati, Simulating Window Behavior of Passive and Active Users, Energy Procedia, Volume 78, November 2015, Pages 621–626. doi:10.1016/j.egypro.2015.11.040.

[73] M. Schweiker, F. Haldi, M. Shukuya, D. Robinson, Verification of stochastic models of window opening behavior for residential buildings, Journal of Building Performance Simulation, 5(1), pp 55-74, doi: 10.1080/19401493.2011.567422.

[74] V. Fabi, R.K. Andersen, S. Corgnati, Verification of stochastic behavioral models of occupants' interactions with windows in residential buildings, Building and Environment, 94 (2015) 371–383, doi: 10.1016/j.buildenv.2015.08.016.

[75] F. Tahmasebi, A. Mahdavi, Optimization-based simulation model calibration using sensitivity analysis, 7th Conference of IBPSA-CZ, Brno, Czech Republic, 2012.

[76] ASHRAE Guideline 14-2014, Measurement of Energy, Demand and Water Savings, American Society of Heating, Refrigerating and Air-Conditioning Engineers, Inc., Atlanta, 2014.

7.2. Tables

7.3. Figures

CV – Farhang Tahmasebi

Professional Background

2013 - 2017	University Assistant, Department of Building Physics and Building Ecology, TU Wien, Vienna, Austria
2011 - 2013	Project Assistant, Department of Building Physics and Building Ecology, TU Wien, Vienna, Austria
2002 - 2011	Project Assistant, Energy, Acoustics and Light Department, Road, Housing and Urban Development Research Center, Tehran, Iran
2001 - 2002	Intern, Energy, Acoustics and Light Department, Road, Housing and Urban Development Research Center, Tehran, Iran

Educational Background

2008	MSc in Low Energy Architecture, University of Tehran, Tehran, Iran
2005	BSc in Architecture, University of Art, Tehran, Iran

Research Areas

Building physics, building performance simulation, energy-efficient buildings, occupant behavior

Publications

https://www.researchgate.net/profile/Farhang_Tahmasebi

Citations

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