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PREDICTING PEOPLE'S OPERATION OF SHADING DEVICES IN OFFICE BUILDINGS

unter der Leitung von

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KURZFASSUNG

Der Energieverbrauch eines Gebäudes wird nicht nur durch die Geometrie des Bauwerks, verwendete Baumaterialien, aktuelle Wetterbedingungen oder die Heizungs-, Lüftungs- und Klimatechnik beeinflusst, sondern maßgebend auch durch das energiebezogene Benutzerverhalten bestimmt, dies beinhaltet die manuelle Bedienung von Fenster- und Beschattungsvorrichtungen. Die Unterschiede der Komplexität des tatsächlichen Nutzerverhaltens und jene der Modellierung werden eindeutig als hauptverantwortlich für die Abweichung zwischen simuliertem und gemessenem Gebäudeenergieverbrauch erkannt. Die Verwendung von zuverlässigen Nutzerverhaltensmodellen ist somit entscheidend für akkurate Ergebnisse in der Gebäudeleistungssimulation. Dementsprechend wurde in den letzten Jahren eine Vielzahl von Nutzerverhaltensmodellen entwickelt. Viele der Modelle wurden aber keinen Validierungsstudien mit unterschiedlichen Szenarien unterzogen und dies resultiert in der ungewissen der Zuverlässigkeit der Systeme. Um dieses Problem zu lösen führt diese Arbeit die externe Bewertung eines weit verbreiteten stochastischen Schattierungs-Betriebsmodells durch. Zu diesem Zweck werden empirische Nutzerverhaltensdaten aus einem Bürogebäude in Hartberg, Österreich, zur Bewertung des Modells verwendet. Insbesondere wird hier die Zuverlässigkeit der Voraussage des Beschattungsmodells ausgewertet. Folgende vorhergesagten und beobachteten Parameter, welche für den Betrieb von Beschattungsvorrichtungen relevant sind, werden verglichen: i) vorhergesagte Handlungswahrscheinlichkeiten und damit beobachtete Handlungen, ii) vorhergesagte und beobachtete Handlungen und iii) vorhergesagte und beobachtete Schattierungszustände. Zufolge der erzielten Ergebnisse unterschätzte das Modell die Schließung von inneren Beschattungsvorrichtungen während es den Einsatz von der Außenbeschattung weitgehend überschätzte. Besonders hervorzuheben ist, dass laut der Ergebnisse das vorhandene Modell keine Muster bzw. Änderungen im Nutzerverhalten, in Hinsicht der Bedienung von verfügbaren Verschattungsmöglichkeiten, in Bezug auf unterschiedliche Jahreszeiten berücksichtigt. Um die Modellleistung bezogen auf vorhergesagte Verschattungszustände zu testen, wurden zwei verschiedene Ansätze, mit und ohne Zustandsrückkoppelung, verwendet. Dies führt zur Erkenntnis, dass die Vorhersageleistung des Nutzerverhaltensmodells ohne Rückkoppelung von modellierten Verschattungszuständen (z. B. über ein autonomes Gebäudeleistungsmodell), nicht korrekt erfasst werden kann.

ABSTRACT

Building energy use is not only influenced by the building geometry, materials, external weather conditions, and HVAC systems but also by the occupant energy related behavior, such as operation of windows and shading devices. In addition, given the complex nature of occupant behavior, modeling occupancy is recognized as one of the major reasons for the potential discrepancy between simulated and actual building performance. In other words, use of reliable occupant behavior models is critical to achieve accurate building performance simulations. Accordingly, in recent years a large number of occupant behavior models have been developed. However, there are major uncertainties associated with the reliability of the occupancy related models as they have not been subjected to validation studies in different settings. To address this issue, the current work conduct an external evaluation of a widely used stochastic shading operation model. To this end, empirical occupant behavior data obtained from an office building in Hartberg, Austria is used to evaluate the model. Specifically, predictive performance of the shade operation model is evaluated by comparing the following predicted and observed parameters relevant to the operation of shading devices: i) Predicted action probabilities and the observed actions, ii) predicted and observed actions, and iii) predicted and observed shading states. According to the obtained results, the model underestimated the closing of interior shades, while it largely overestimated the deployment of exterior shades. More importantly, the results suggested that the model could not capture different seasonal patterns of occupants' operation of shades. With regard to the predicted shading states, two different approaches were adopted to test the model performance. However, it is concluded that, without including the model's feedback (for example via a building performance model) the predictive performance of the occupant behavior model cannot be properly captured.

Keywords: occupant behavior, shading devices, model evaluation, stochastic model

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1 INTRODUCTION

1.1 Overview

Predicting people behavior in building indoor environments is a topic that is conducted throughout multiple studies worldwide. Collecting and analyzing data on building users' interactions with the building control systems and devices can help development of the behavioral model for integration in building performance simulation applications. With more realistic simulation outputs, the operational buildings systems for indoor environmental control can be more productive and more energy efficient (e.g. Bourgeois et al. 2005, Hunt 1979, Love 1988, Mahdavi et al. 2006, Newsham 1994, O'Brian 2016). People affect thermal indoor environment just being in the room without any actions by emitting sensible and latent heat (as a heating source), but mostly their actions, operation of the building systems for heating, cooling, ventilation, lightning and shading are affecting indoor environment. In addition, many studies (e.g., Gunay et al. 2015, Cheng and Soh 2016) have outlined the problems in use of existing occupant behavior models. Specifically, it has been stated that the behavior models need to be validated and evaluated more rigorously and in different settings in order to better support the building performance simulation tools that predict energy use in buildings (Mahdavi and Tahmasebi, 2016).

The main goal of this study is an evaluation of a widely-used stochastic shading operation model (Haldi and Robinson 2010) that will be conducted in three approaches: i) Predicted action probabilities and the observed actions, ii) predicted and observed actions, and iii) predicted and observed shading states. The results from aforementioned approaches will provide better understanding of the model predictive performance. Evaluation process is based on the data collected over a nine-month period of monitoring occupancy, building systems, along with interior and external environment parameters in an office building in Hartberg, Austria. In total, there are 14 windows that were closely monitored, all having interior and exterior shading devices (curtains and Venetian blinds). This data, will be used to implement and evaluate the aforementioned shading operation model. Thereby, in accordance to the model formulation, the key parameters are indoor and outdoor illuminance, occupancy, and shading state.

This thesis is structured in terms of four chapters. Chapter 1 is going to reflect on the researches in the occupant presence and behavior models, manual operation of shading devices, shading operation models and evaluation of the occupant' behavior models. Chapter 2 gives details about case study, methodology, data collection and implementation. Chapter 3 is dedicated to the results and discussion and chapter 4 is conclusion of the study with the perspectives on the future research.

1.2 Motivation

Most people when refer to energy use in buildings think about factors such as building envelope, geometry, climate, energy and service systems, building operation and maintenance. In the past, there have been a substantial advancement in these areas. The shortage in progress of understanding of building energy use is the relevant occupant behavior in buildings. According to the International Energy Agency (IEA), building energy consumption represent a great percentage of the worldwide energy consumption with the extraordinary potential for preservation. To deal with this issue, building energy simulations, as a cost effective method, is gaining global applications to provide support in energy efficient design and operation of buildings. In most office buildings, occupants can operate control systems to make more desirable indoor comfort. Such systems are windows, shades, luminaries and HVAC. For the accurate prediction of the building performance, it is necessity to understand these actions to have effective operation of the service systems. Numerous studies have shown that occupant behavior influences energy use in buildings and it is a main source of uncertainty in predicting building energy use (Yan et al. 2015, Mahdavi and Tahmasebi 2015, Gaetani et al. 2016).

Furthermore, reliability of building performance models is very important in reducing energy use in the sustainable energy future. Traditionally, simple schedule based methods have been used to account for the effects of occupants. However, newer research has shown that these methods often result in large differences between the modeled and actual energy use of buildings. As one of the environmental control systems that is operated by occupants, shading devices play a central role in the heat gains of a building and therefore on its energy performance. It is thus useful to predict their use by occupants, particularly where automatic controls are lacking. In addition, in dynamic building performance simulations, knowledge of shade positions is critical to correctly assess the availability of daylight, overheating risk and the visual comfort of occupants.

The importance of this research is to address the challenges in validating an occupant behavior model that can be used in building performance simulation. It goes without saying that with validated occupant behavior models, the simulations tools could imitating people’s behavior in the buildings more realistically and thus simulating the indoor environment and energy use more accurately. Besides, such models can be a great support for the further development of the automated building shading systems.

1.3 Background

1.3.1 Occupant presence and behavior models

Over the last four decades, many studies have focused on the issue of occupant behavior in office buildings. Occupants’ behavior in buildings have a great influence on overall energy consumption and predicting building energy use. Their presence and interactions with building systems have large impact on indoor environment (Mahdavi 2015).

To measure such impacts, both empirical and simulation-aided studies have been carried out. In one study, Azar and Menassa (2012) observed that energy models of office buildings’ in different climatic zones in USA are highly sensitive to occupancy-related behavioral parameters. In particular, Yang et al. (2014) presented a study where an observation based occupancy schedules that are used in application of HVAC systems in low rise office buildings can save significant percentage of energy in comparison with default occupancy schedules.

Clevenger and Haymaker (2006) considered uncertainty in occupant behavior in building energy models, utilizing different occupancy schedules and ecological indicators and found that the energy utilization varied 150% if the occupant-related information sources were amplified and minimized. Guerra Santin et al. (2009) concentrated on the impact of occupant behavior toward heating system, and found that their behavior had big influence on heating energy consumption. It can be reasoned that occupant’s presence and interaction on building systems fundamentally influence the energy performance predictions regardless of the climate conditions, the building envelope and systems.

Given the importance of occupant presence and control oriented actions, many efforts have been made to provide reliable input information pertaining to occupants for building performance simulation models. Occupant behavior models, are developed to equip designers with the tools to better predict the energy performance of buildings (Yan et al. 2015). To ensure that models are applicable in design, they should be capable of accurately predicting occupants’ energy-related behavior in buildings other than those from which the data have been obtained. This obliges models to catch significant properties in the occupants behavior, (e.g., randomness, diversity among individuals and complexity in factors aforementioned), without the distinctiveness that the source information could present. For the comprehensive use, occupant models ought to be functional, vigorous, and have a sensible number of data sources that are promptly accessible in building performance simulation tools (Yan et al. 2015).

In general, there are three broad approaches for the representation occupants in building performance models: Typical schedules, rule based model, and stochastic models.

Static schedules

Occupants in building simulations are generally characterized according to static calendars (Hoes et al. 2009). General assumptions are connected to portray occupant presence in a building or room. This additionally identifies with the occupant activities in the building. User profiles presents both occupancy and actions, for example, portraying the utilization of lighting during the working hours, from 8 o'clock until 18 o'clock (Hose et al. 2009).

This interpretation does not appropriately capture the impact of occupants on building energy utilization and indoor environment (Dong and Lam 2014). In reality user behavior is much more complex. For instance, it relies on building design or climate. Moreover, as in this approach averaged values are used, optimization for sustainable solutions is less sensible (Rijal et al. 2007). As a general rule, in building performance models there needs to be a dynamic interaction between building systems and occupants so that more suitable plans can be recognized. For example, without displaying occupant utilization of windows or blinds, simulation results may demonstrate that increasing the window area will necessarily increase daylight usage (Yan et al. 2015). Nonetheless, in reality, vast windows may only incite occupants to close blinds and solely depend on electric lighting because of glare issue. Consequently, it can be argued that utilization of static schedules to represent occupants in building simulation fails to mirror the dynamic connection between the occupant and building environmental control devices.

Rule-based models

The easiest approach to emulate occupants' interactions with building system has been the use of simple rules. For example, in the widely used simulation tool EnergyPlus possibilities are considered to represent the operation of windows with one or two temperature thresholds. More precisely, using this modeling approach, all windows in the building are opened if the indoor temperature is, for example, above 26 degree Celsius and indoor temperature is higher than outdoor temperature. Needless to say, there is no probability associated with the rule based models. That is, as soon as the conditions are met, all the devices connected to the model are operated.

Stochastic models

To capture the dynamic connections between buildings and the occupants, more recently a large number of occupancy-related models have been created form long term observational studies (Gunay et al. 2013). A few stochastic models have been created to portray windows operations (Anderson et al. 2013, Lee 2014), blinds (Zhang 2012, Newsham 1944, Reinhart 2002, Haldi and Robinson 2010) and lighting (Boyce et al. 2006, Inkarojrit 2005). Complexity of occupant presence and behavior in building environment has its difficulties for implementation in building performance simulations. Number of studies have proposed that stochastic models predict with more reliability giving factual indicators for building performance. Thereby, these models not only represent the occupant's behavior in a probabilistic manner, they also integrate a variety of explanatory variables to better capture the inherent complexity of people behavior. However, the existing stochastic behavior models are commonly based on limited sets of observed data (Mahdavi, 2016).

Figure 1 presents stochastic occupant behavior models categorized based on three principal forms (Yan et al. 2015):

1. Bernoulli process
2. Discrete-time Markov chain
3. Survival analysis

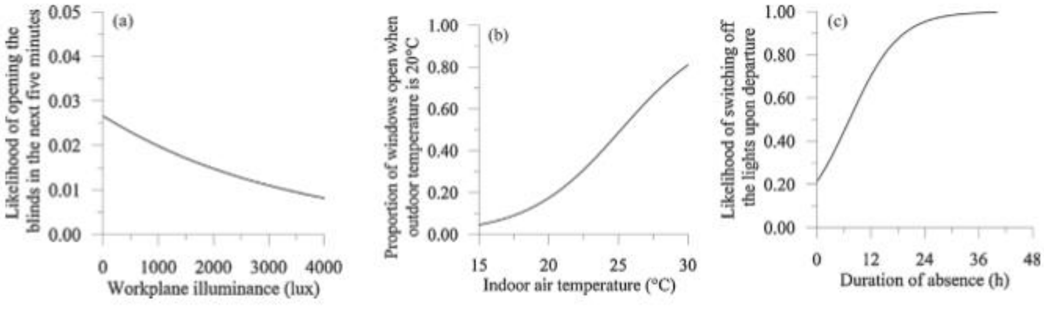

Figure 1 Example illustraton of different stochastic occupant behaviour mdoels: a) discrete-time Markov model b) Bernoulli model and c) survival model (source: Yan et al. 2015)

Bernoulli processes (Haldi and Robinson 2008), are maybe the most straightforward of stochastic models in which the probability of an action or state is not reliant on the past state. The favorable position of the Bernoulli processes is that the scope can be effectively connected to the entire building level (e.g., the part of lights are on or occupants are in their homes). This is helpful for energy modeling at the large scale, however does not portray singular behavior/comfort and it doesn't foresee the planning of individual practices. As beforehand mentioned, in early plan such an approach might be valuable since Bernoulli processes are computationally productive and don't require as much data.

Markov chains (Haldi and Robinson 2009), as opposed to Bernoulli processes, rely on the past state to foresee the likelihood of a state transition. This is helpful for portray people's activities and the derivers for those activities. In any case, Markov chain models cannot be connected to large scale of occupants, and hence computational resolution scales straightly with the quantity of occupants demonstrated. An expansion of Markov models utilizes agent-based modeling in which occupants can have a more extended memory. These models determine how occupants connect with each other and with their surroundings (Axtell et al. 2001). Agents' details incorporate their behavioral rules, memory, assets, basic decision making processes, and any guidelines for changing current behavioral standards.

Survival analysis (Reinhart 2004, Haldi and Robinson 2009, Haldi and Robinson 2010) was initially used to foresee the likelihood of to what extent some individual will live. In general, survival analysis is utilized to appraise the time until an action happens. A similar technique can be connected to occupant behavior models. For example, survival models can indicate to what extent a building is probably going to stay unaffected by occupants. Unlike the past methodologies, survival analysis is a continuous time approach, implying that they may determine some time duration of elapsed time before an event occurs.

1.3.2 Manual operation of shading devices

A certain number of studies regarding manual operation of shading devices in office buildings have been made till now. They were investigating occupants' operation of shading systems and the influential elements such as external environmental factors, time and date as well as building orientation, etc. The summery of the major findings will be presented in the fallowing.

In case of operation of shading that depends on the façade orientation Rubin et al. (1978) conducted an investigation of Venetian blinds in Maryland USA. The focus was on the north and south facades of an office building. They used photography method that helped them register the state of hundreds of windows' shades. The main focus of the study was to correlate the façade's orientation with the quality of the view and seasonal changes. In spite of those findings, they couldn't relate the sky conditions and time of the day with the states of the shading devices. The conclusion of the research was that occupants in the southern offices tend to use more shades (to block direct sunlight) than the ones in northern offices. Less than 10% of the shades were reset after the initial settings. Occupants usually were not manipulating shades after the first adjustment.

A decade later, Inoue et al (1988) conducted a study in Tokyo, Japan. The investigation was carried out in four high rise buildings that used manual controlled venetian blinds as their shading systems. The focus was to capture photos of all four facades synchronously and measure direct and defuse irradiance at the same time. The data was collected every hour over a three-week period. The results of the study showed that shading operation was proportional to the depth of sunlight penetration into the offices (see Figure 2). Direct solar irradiation on facades had a threshold of 50 W.m^{-2}. When this value decreased the blinds were not reopen and the reason can be of lost visual connection with the external environment.

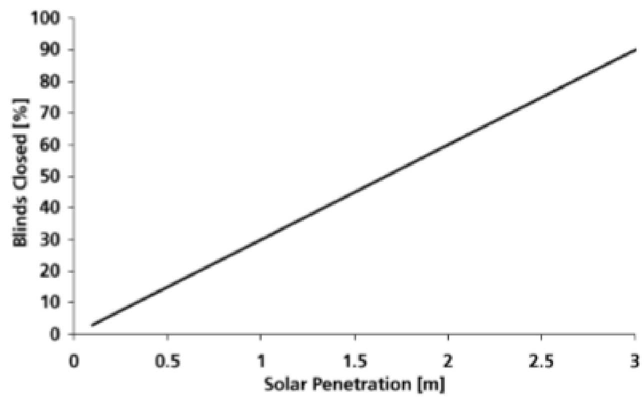

Figure 2 Percentage of closed blinds in relation to direct solar penetration in an office on SSW façade (source: Mokamelkhah 2007)

In Figure 3, the curved line presents the correlation of the percentage of the closed blinds and the quantity of the incident solar radiation through windows on certain façade. The relation between shade occlusion and incident illuminance form a curved line, that represents times when incoming solar irradiance decreases but the number of shade's occlusion rise. Also, the changes in blinds occlusion depended on façade's orientation. In most of the cases, the eastern façades were closed in the morning with the rising sun, while the western shades were closed in the afternoon.

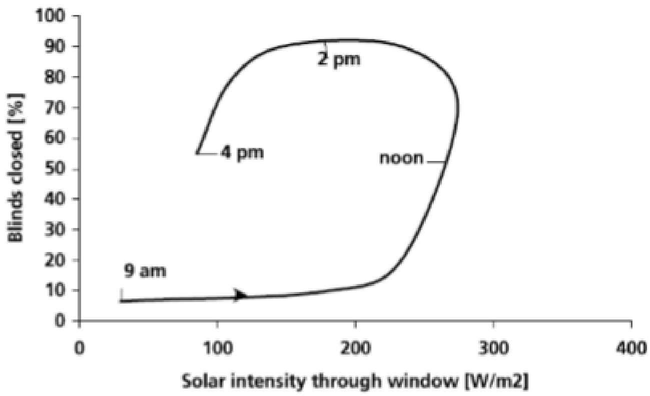

Figure 3 Percentage of closed blinds in relation to the vertical solar irradiance on a SSW façade (source: Mokamelkhah 2007)

Lindsay et al (1993) monitored five office buildings in UK. His approach was to record the data with time-lapse photography using video camera twice a day as well as recording occupancy in 2-hour-time-steps. Other external environmental information such as temperature, direct and diffuse irradiance, sky conditions were recorded in one-hour time-steps together with shading states. All data was monitored over period of 4 months. Total of 259 windows were monitored, where 105 windows were on a northern façade, 100 on a southwestern façade and 54 on a southern façade. The findings are as fallowed:

- Blinds' states do not change from fully open to fully close (0-100%). In most cases shade manipulations were around 40%.
- Solar radian and sun position were in direct correlation with the number of shades operations.
- Average rate of the shades was on the minimum and in correlation with incident direct sunlight to the façade. Occupants would mostly closed the shades in the morning and opened them when they are about to leave the offices.

Pigg et al (1996) investigated the usage of the shades in 63 offices. The results are:

- 36% of the occupants never operated the shades.
- Shades operation in north façade is significantly lower than south façade.
- 37% of his study subjects stated that in order to reduce glare on their computer screen, they operate the shades.

Farber et al (1992) concluded in a study in UK that a threshold of 300 $W.m^{-2}$ solar radiation would cause a change in the shade position, Newsham (1994) investigation of a single office building in UK revealed similar results. When solar radiation is above a threshold of 233 $W.m^{-2}$, occupants fully close the shades and the shades will be remained closed until the next day.

1.3.3 Shading operation models

One of the first attempts to model occupant's behavior toward shading systems is performed by Reinhart and Voss (2002) while developing the Lightswitch-2002 algorithm. The model using this algorithm automatically controls blinds and light on a five minutes time step. It identifies two different types of behavior regarding blinds usage; static and dynamic. Static behavior represents that the blinds are permanently lowered while dynamic behavior indicate that blinds are regulated on the daily basis. The automatic blind control system ensured that the blinds were usually retracted when ambient daylighting levels were low. Irradiance of $50W/m^2$ on the workplane is the threshold for the blinds to remain lowered otherwise they are kept open.

Sutter et al. (2006) in their study of shading systems in task offices observed that blinds are either fully raised or fully lowered. The occupants would not raise the blinds until the illuminance is very low. In cases when the illuminance level is higher than the threshold in which they would raise them is called hysteresis phenomenon and it is reported in this study. However, the vertical global illuminance is important variable in logistical function that indicate the percentage of the blinds being raised. The suggestion of other indented variable is temperature which can affect the function.

Lindelof and Morel (2008) using Bayesian analysis, analyzed actions on blinds performed in the LESO building in Lausanne, Switzerland to infer a probability of illuminance distribution of visual discomfort. The discomfort probability for illuminance below 200 lux is in range from 0.5-1.0 (classifying as high), whereas for the illuminance of 500 lux, the discomfort is about 0.3. For the values above 500 lux, the discomfort gradually rises and at 3000 lux reaches maximum value of 1.0.

Mahdavi et al. (2008) observed three office buildings in Austria, with regard to user control actions. Conclusions of this study highlight a number of important points. First, the occupancy of the offices was very low, and the patterns were greatly diverse in the studied buildings. Second, there was not a strict relationship between occupancy and lighting operations. The probability of turning the light on in both time intervals (arrival and intermediate) was greater when the horizontal illuminance levels on the workstation were less than 200lx. Third, shading states were in direct correlation with intensity of the incident solar radiation. Depending on the orientation of the façade, there were more variability in shade positions. The suggestion was made that if the occupancy sensors were installed together with daylight responsive dimming devices, the electrical energy use could be reduced up to 70%.

Inkarojrit (2008) tested a model formulated as logistic probability distribution from the measurements obtained in two office buildings in California, USA. The model had a range of different variables. For the final model he maintained four variables which are vertical solar radiation, average and maximum luminance of the windows as well as self-reported sensitivity to brightness. However, this model was based on the occupant's behavior upon arrival therefore was not supported the development of a comprehensive model.

1.3.4 Evaluation of the occupant's behavior models

Recently, a large number of studies have concentrated on the capability of probabilistic techniques toward representation of occupant behavior. In this regard, an expressed goal has been to overthrow static schedules and rule based activity models in performance simulation. Various models have been and are being integrated in building performance applications. Nonetheless, it is argued that as these models have not gone through extensive evaluation process and the reliability of their predictions can be questionable (Mahdavi and Tahmasebi 2016). Models have been on occasion rashly advanced as substantial and dependable, in spite of needing exact proof. Be that as it may, it must be done carefully and systematically, keeping in mind that result can vary, due to uncritical execution and utilization of a wide range of inadequately tried behavioral models.

1.3.4.1. Simulation scenarios

Recent studies outlie a number of uncertainties in the use of existing occupant behavior models in different settings (Mahdavi 2016). In building performance simulation one can focus on different performance indicators depending on the need for simulation. Some simulations can target specific buildings parts, for example, thermal bridges analyses (focusing on one floor of a multi-floor building). Others are based on the whole building or bunch of buildings for larger scale simulations (Mahdavi 2016). There was a misunderstanding that more advanced stochastic models are superior to the old simple rule-based models in all simulation scenarios.

However, for example, Mahdavi et al. (2016) showed a non-stochastic plug load model provide more reliable results - as compared to stochastic models - in predicting annual plug loads. Likewise, Mahdavi and Tahmasebi (2015) showed that for short-term prediction of occupancy, non-stochastic models perform better than the stochastic ones.

Also according to Gaetani et al. (2016) the task is to determine which model performs best for each simulation scenario. From the dictionary, the definition of *fit-for-purpose* is something good enough to do the job it was designed to do. This means that user has to choose the model based on the specific case. There are many factors that influence the choice of occupant modeling: object-related factor, aim of simulation, performance indicator and phase of building lifecycle. These factors have their sub-categories such as: building function (single family house, office, hospital, etc.), building characteristics (conditioned, HVAC system, main orientation), interaction of building with outdoor (percentage of facades, glass type), interaction building/user (lighting control, thermostat, and blinds control), design, energy consumptions (heating/cooling energy demand), load (max heating/cooling/lighting load), visual comfort and etc. All these factors influence on modeling technique that will be used in simulation.

Depending on the complexity of the model, different approach and choice of software should be used. When simulating single family house vs. large building complex the energy simulation model will be much simpler. This approach also influents the selection of behavior model that determines occupant scenario. The decision to use an occupant behavior model at all, and which specific model is selected, has important consequences on the evaluation of a building's energy performance (Mahdavi, 2011).

1.3.4.2. Application scenario diversity

Since the model evaluation is a complex process, the reliability of the building performance simulation does not only depend on the validity of the mathematical algorithms, but also on the correctness of the input assumptions (Yan et al. 2015). Application scenario's diversity is a significant category when talking about occupancy-related model options. The project's phase is determining what kind of simulations is needed (preliminary or detail design, system and/or operations design support). Furthermore, spatial view is one more category that should be considered. There are single-zone and multi-zone scenarios that can be run in different intervals: e.g. 10 minutes, hourly, monthly simulations. Application scenarios could be additionally recognized as far as a definitive utilization of the computed parameter. An example is to create an energy certificate, correlation of option plans at a specific phase of the building configuration process, plan and estimating of structures' mechanical hardware, real-time utilization of intermittent element recreations in a prescient building frameworks control schedule.

In the previous decade, building scientists has been developing more advance occupant models founded on observed data. It has been disputed that occupants ought to be presented and displayed stochastically instead of deterministically (Nicole 2001). That means that occupants are probably not going to react similarly to a given arrangement of conditions in a machine-like way due to numerous complexities to their basic decision-making process. However, even the stochastic models in the common application procedures tend to suppress occupant behavior diversity (inter-individual differences amongst attitudes, preferences, and habits) (Mahdavi and Tahmasebi 2015; O’Brien et al. 2016). Diversity is rarely recognized in existing occupant models. Therefore, comparing vulnerability of building performance simulation predictions might be incredibly undervalued. Diversity can provide a smoothing effect on peak load (O’Brien et al. 2016). An example, if a model assumes that all occupant arrive are the same time and turn on lights and appliances while heating and cooling system are scheduled to be activated simultaneously. In this case, the peak energy load of the building would be higher than if the arrivals are personalized. Detail occupancy data is rarely available in order to develop an occupant behavior model, systematic statistical analyses of existing data can enhance development of occupancy diversity in respective modelling efforts (Mahdavi 2015). While trying to present occupants behavioral differences, Haldi and Robinson (2010) analyzed individual behaviors by assessing diverse regression parameters for all members in the study. In any case, this approach just explores varieties among the observed occupants and does not give summed up results. That is, the thinking behind the varieties stays unclear and related logical factors can't be recognized. Learning of the assorted qualities among the occupants and comparing models additionally could realize an appropriate harmony between simulation resolution and computational expenses by selecting the ideal specimen estimate and focusing for the reasonable complexity level in occupancy related models.

1.3.4.3. Evaluation process

The state of the art in modeling, both occupancy and actions (with concern on the evaluation of the models), is not developed enough as there are many factors to consider. Late reviews (Gunay et al. 2014, Gunay et al. 2015, Yan et al. 2015, Tahmasebi and Mahdavi 2016, Wang et al. 2016) highlighted general issues and constraints connected with the advancement of occupant behavior models regarding their accuracy and relevancy, including the evaluation process and the principal statement of predicted parameters. To build up the accurate evaluation process, it is obligatory for a significant level of clarity and consistency from development to the implementation of the model. The accompanying arrangement of essentials, as to the assessment of occupancy and activity models, are properly gathered, organized and translated observational information that are crucial for development and evaluation of the resulting occupancy and activity model. Aside from the standard technical requirements (sensory infrastructure, data quality, sample size and sampling frequency, etc.) and statistical treatment quality, psychological and social considerations (such as those pertaining to the Hawthorne effect) need to be explicitly addressed (Yan et al. 2015).

The nature (causal, information driven, and so forth.) and the spatial and transient determination of the models that are to be assessed must be obviously characterized and doubtlessly expressed. In like manner, the intended application must be indicated (building design, code compliance, building systems sizing, building control processes, etc.) as it has solid ramifications for the logic of the evaluation strategy. The objectives of the evaluation process must be unmistakably specified (Yan et al. 2015).

The standard logical criteria and strategies in model evaluation must be considered and complied with. Sufficient thinking must be given with regards to the motivations to deviations from such due methodology. Instances of relevant practices include, for example, the separation of data sets for model development and model evaluation (Mahdavi 2015). The most conclusive evaluation of a predictive model can be achieved if two completely different data samples are used for its derivation and validation (Haldi and Robinson 2010). Additionally, collecting new data is regularly an excessive procedure because of the required equipment and time, while the choice of fitting specimen estimate for estimation time, frequency, and the quantity of observed occupants remains an issue for discussion (Sadeghi et al. 2017). Analysts in the building performance simulation area and those included in the building occupancy modeling specifically have an expert commitment to apply the most noteworthy conceivable benchmarks of logical request in directing perceptions, creating models, and performing evaluations. The report of evaluation must document all the model specifics and applicable limitations for the benefit of those implementing the model within simulation tools as well as those using such tools toward practical application of building performance.

1.4 Research questions

Given the aforementioned background, the current thesis deals with external evaluation of a widely-used stochastic shade operation model as a case in point to address a number of essential questions on the reliability and evaluation procedure of occupant behavior models: To which extent does an existing shading operating model can represent the occupant interaction with shading device in a new setting? Is the model performance influenced by the seasonal variations? Does the model performance vary based on the type of shading? The model's predictions will be evaluated though aspects of actions probabilities, shade states and shade actions.

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2 METHOD

2.1 Overview

The focus of this study is to evaluate a shading operation model with data measured in an office building located in Hartberg in Styria, Austria. The data was collected through 9 months of observation of occupants' operation of shades together with indoor and outdoor environmental parameters. The model that is being evaluated in this study is an existing stochastic model of occupants' interactions with shading devices developed by Haldi and Robinson (2010). In this section, besides detailed explanation of the building and the occupant behavior monitoring campaign, the model and its sub-models are described and illustrated to provide a better understanding of the model's procedures to determine shade operation actions and resulting states. This is followed by the explanation of the implementation of the model and a threefold evaluation strategy to assess the model predictive potential in the new setting. .

2.2 The monitored building

The governmental office building "HB" located in Hartberg, Austria has two parts with different construction types (old and new construction). This 4 floor cube building has 3463 m^2 ground area.

This study is concerning old block whose façades are mainly made of concreate and glass, whereas the new block's façades are made of glass supported by aluminum frames. The building and offices of this study are orientated northeast.

A characteristic feature of this building is its use as governmental service unit. The occupants arrive rather early in their offices and regularly receive clientele with administrative questions and requests.

Figure 4 General view of the HB building with indication of the observed offices (source: Mokamelkhah 2007)

The data was collected over a period of nine months from November 17th 2005 until July 20th 2006. The measurements were conducted in six offices situated on first and second floor in the northeast part of the building. The offices contain two double occupancy in roughly 28m^2 floor areas and four single occupancy offices in 20 m^2 areas each. The workstation, 10 in total, are equipped with computers and task lights where some of them have printers as well. The occupants perform both screen-based and paper-based tasks. The furniture in the offices, except chairs, is made of light brown wood (cupboards and bookshelves). The walls and ceilings have white color and parquets covering the floor. The offices have either two or three windows.

Figure 6 shows interior views of two offices on the first and second floor. Figure 5 presents the schematic layout of the three offices on the second floor.

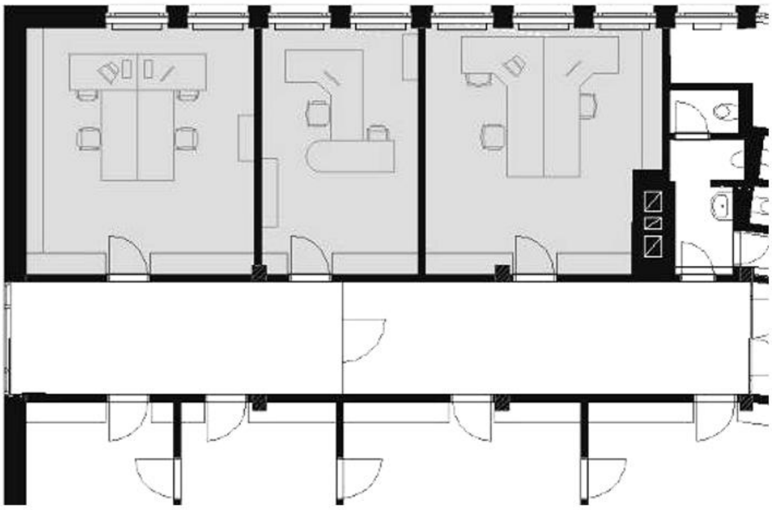


Figure 5 Layout of the sample offices with single and double occupancy (source: Mokamelkhah 2007)

The offices are equipped with the fallowing systems. Two rows of luminaries with four or six fluorescent (58W) lamps divided into two circuits and are manually controlled by two switches near the entrance door. The heating system is based on radiator units located under each window and users can change the settings for the adjustment of temperature. There is no cooling and air conditioning system in the offices. The occupants can have natural ventilation by opening the windows.

Shading system contains of two manually operable parts to control daylight: external shades and internal curtains. The windows are double-glass in two or three modules that are manually operable in two positions tilt/turn.

Figure 6 Left: Double occupancy interior view, Right: Interior view of the single occupancy room (source: Mokamelkhah 2007)

2.3 Data Collection

The measurements were collected both for internal and external environmental parameters. The intention was to observe users control actions towards shading devices and the condition under with those actions occur. The collected data was analyzed to explore hypothesized relationships between the nature and the frequency of the control actions on one side and the magnitude and dynamics of indoor and outdoor environmental changes on the other side.

The data collection in HB was done in nine months starting November 17th 2005 until July 20th 2006. The interval for logging all internal/external environmental parameters was 5 minutes except for the image photography that was every 10 minutes. The data was downloaded regularly every 30 to 40 days.

2.3.1 External parameters

To obtain external environment parameters such as temperature (°C), wind speed (m/s), global horizontal irradiance (W.m^{-2}) and relative humidity (%), a weather station was used that was mounted on the top of the building (Figure 7). The local weather data is structured in 5 minutes intervals. Sensors and data loggers were fixed on a vertical mast on the weather station. Figure 7 shows the weather station used in this study. Sensors' accuracy is presented in Table 1.

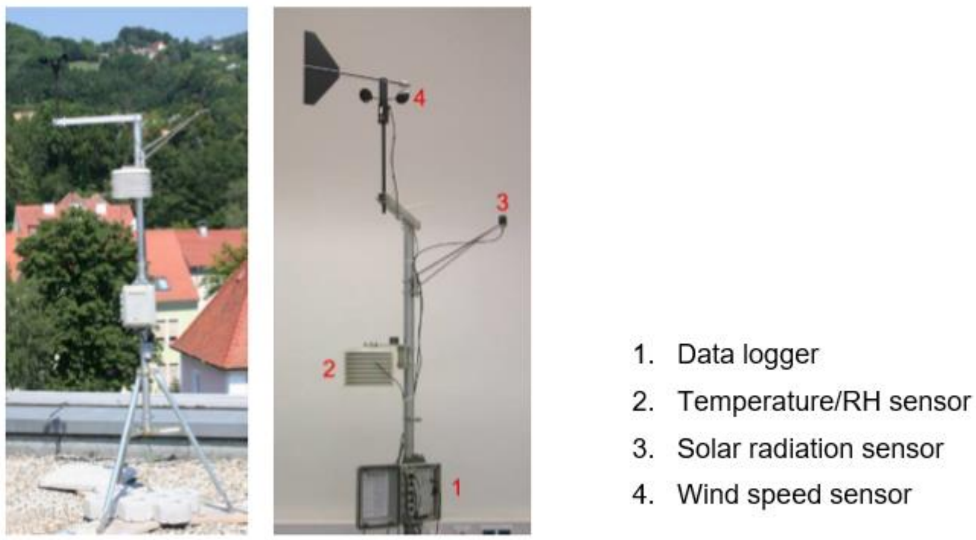


Figure 7 Weather station placed on top of the building (left) (source: Mokamelkhah 2007)

Table 1 Specification of the Weather Station sensors

Sensor	Measurement range	Accuracy
Solar radiation	0 to 1280 W.m-2	±10 W.m-2 (± 5%)
Wind speed	0 to 45 m.s-1	± 1.1m.s-1 (± 4%)
Temperature	-40°C to 75°C	± 0.7°C at 25°C
Relative humidity	0 to 100% between 0°C and 50°C	± 3%; ± 4% in condensing environments

2.3.2 Internal parameters

In order to collect internal environmental parameters different types of data loggers were used. These devices were placed under the light fixtures and across working stations. The collected data included temperature (°C), light intensity (lx), relative humidity (%), occupancy and state of indoor shades.

Indoor measurements were obtained with Hobo logger attached to the wall approximately next to the workstation. Data logging was done every 5 minutes for temperature, relative humidity and light intensity. Downloading data was done every 30-40 days with specific computer software. The software was used to read out data, launching sensors for the next measurement and see the status of the logger.

The measured parameters by the sensor are:

- Room temperature [°C]
- Relative humidity [%]
- Light intensity [lx]

Figure 8 shows the sensor/logger and its components. Key specifications of the sensor/logger are presented in Table 2 (Onset 2007).

The sensors were installed horizontally on the workstation. Figure 9 shows the location of the HOBO sensor in the offices on the first and second floor.

Table 2 Key specification of the HOBO sensor

Internal sensor	Measurement range	Accuracy
Temperature	-20°C to 70°C	± 0.35°C from 0°C to 50°C
Relative humidity	5% to 95%	±2.5% from 10% to 90%
Light intensity	12 to 32.000 lx	

1. Relative humidity/temperature sensor
2. Reset button
3. USB port
4. LED operation indicator
5. IL luminance sensor

Figure 8 HOBO sensor (source: Mokamelkhah 2007)

Figure 9 Position of the HOBO sensor in one occupancy (left) and double occupancy room (right) (source: Mokamelkhah 2007)

IT-200 loggers are produced by Wattstopper Inc., which are used to log occupancy and state of the artificial light (see Figure 10). Components of this loggers are as fallow:

1. Red LED blinks when occupancy is detecting
2. Green LED blinks when lighting is ON
3. Test button activates LEDs for 1 min during which sensitivity is set and proper location for occupancy detection is verified
4. Button adjusts the sensitivity of the light sensor
5. IR sensor detects movements of the occupants
6. Adjustable light pipe observes lighting level
7. Reset button
8. Serial port connecting to PC

Figure 10 IT-200 Occupancy and state of the light sensor (source: Mokamelkhah 2007)

Key specifications:

- Connects to PC for data retrieval via cable
- Covers up to 45 m^2
- It's battery operated (lithium), average battery life ~10 years
- Stores approximately 4000 entries

The IT-200 records a log entry whenever there is a change in either occupancy or lighting status and stores a detailed history of these events for retrieval by computer. It utilizes passive IR technology to detect occupancy. It observes the luminance through a plastic pipe to determine if lights are ON or OFF (Wattstoper 2006). The loggers were installed so that the lens had a clear view of the workspace and the light-pipe aimed towards the nearest light fixture (see Figure 11).

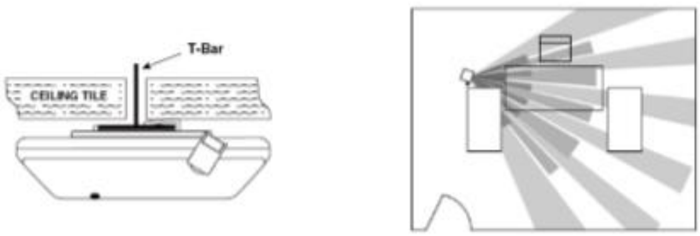


Figure 11 Occupancy and state of the light sensor (source: Mokamelkhah 2007)

Using passive infrared technology (PIR) the occupancy sensor can monitor up to 45 m^2 of an area. To set the interval for the sensor, we considered two types of limitations, namely storage and accuracy. As a trade-off it was agreed to work with 5-minute intervals.

The requirement for the light sensor is not to be exposed to direct sunlight, otherwise it can produce unreliable results. Limitations of the indoor data logger is the memory storage, which can store measurements up to 50 days (with 5-minutes interval). For that reason, the data was regularly downloaded every 30 to 40 days.

2.3.3 Monitoring shading devices

Obtaining data for shading devices was done with three high resolution digital cameras. Compact flash memory cards (2GB) were used to store pictures that were taken in preset time intervals. These cameras were placed in metal boxes to be protected from environmental damages (see Figure 12). Maximum number of the pictures per camera was 1800 in one session. The pictures were taken every 10 minutes and thus with the memory of 2GB it was enough space to cover 10 days. Pictures were downloaded regularly to free the memory card in order to have continuous set of data.

Figure 12 Camera in aluminum box with power supply (source: Mokamelkhah 2007)

2.4 The selected shade operation model

For the purpose of this study, as an example for recently developed stochastic occupant behavior models, a shade operation model was selected that is introduced by Haldi and Robinson (2010). Two main motivations for creating this model are:

- Development of control algorithm to allow automated system to adjust in order to optimize solar heat gains;
- Prediction of actions performed by occupants in order to integrate them in the building performance simulation tools.

They were monitoring and collecting data from the LESO-PB building in Lausanne, Switzerland. Characteristic for these offices is that there are two blinds (upper and lower) operated with switches (closing/opening) thus the occupants could choose to shade windows in desired fractions. Over 6 years of monitoring the fallowing data was measured in 5-min time steps:

- Temperature: Indoor and outdoor (roof)
- Indoor horizontal workplane illuminance
- Outdoor global horizontal illuminance, outdoor global and diffuse horizontal irradiance
- Occupancy
- Lower and upper blind position

In development of the shading operation model occupancy, indoor and outdoor temperature, indoor horizontal workplane illuminance and outdoor global horizontal illuminance are considered as potential explanatory variables.

According to the observations in the study of LESO-PB building, Haldi and Robinson created an algorithm that is simulating the usage of the shades. The following steps are implemented in the model:

- Checking of the occupancy status as the main condition for the action to happen. In the intervals where the occupancy is not positive, meaning there is no occupant present at the time, the shade remain constant as in the previous interval.
- The probability of closing and opening of the shade are calculated according to Equation 1.
- If the probability of closing the shades is bigger than probability of opening, Monte-Carlo method is used on closing probability to establish whether a closing actions is happening or not. In the case when the closing action is

not happening, the Monte-Carlo method is determining whether an opening action is occurring using opening probability.

- When the probability of opening is bigger than the probability of closing, the procedure of the previous step is inverted.
- If the model predicts an action, using Monte-Carlo method, the model is to determine whether the shade is to be set up to a full extent or not, through probability of fully closing and opening, $P_{fullclose}$ and $P_{fullopen}$. When the action is not to the full extent, using the fitted Weibull distributions the new shaded fraction is determined.
- As the model is predicting shading actions for both internal and external shades, the procedure is performed sequentially for each shade.

For an easier understanding of the procedure, Figure 13 shows the steps used in the algorithm.

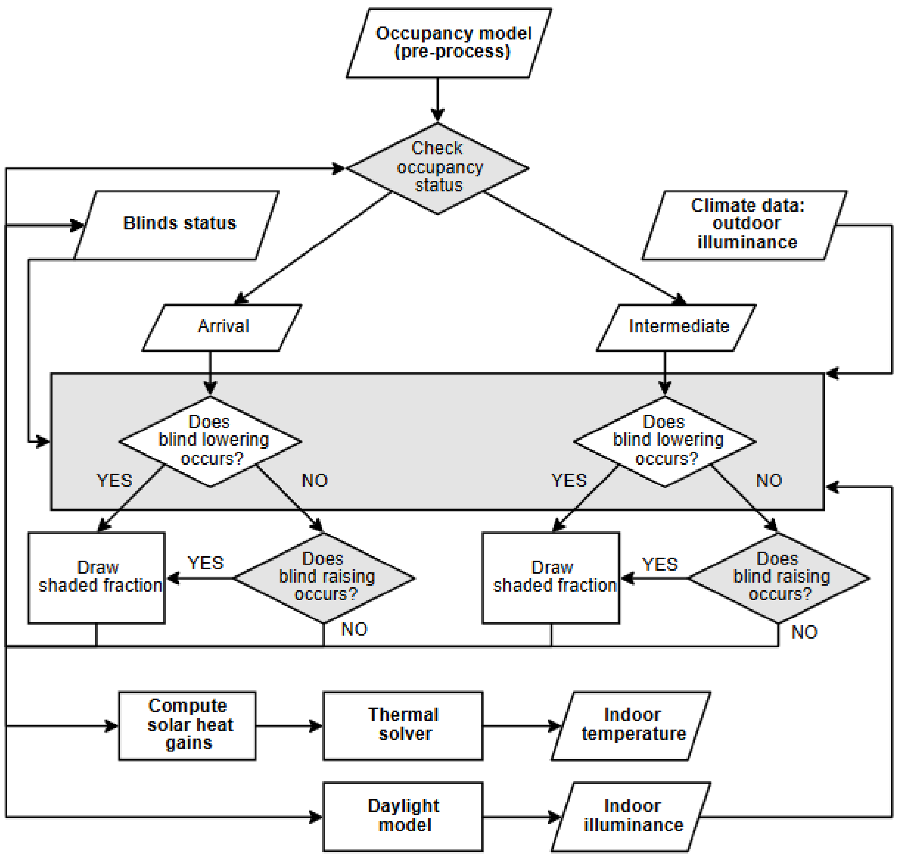


Figure 13 Algorithm that is used in the shade operation model (source: Haldi and Robinson 2010)

The action probabilities are based on logistic regression (Equation 1):

$$Logit\ (P) = \log\left(\frac{P}{1-P}\right) = \\ = a + b_{\theta in}\theta_{in} + b_{\theta out}\theta_{out} + b_{Ein}E_{in} + b_{Egl,hor}E_{gl.hor} + b_bB_b \quad (1)$$

where *a* and b_i are the regression parameters (Table 3). The statistically significant independent variables in the final model are selected using forward selection, as the simplest data-driven model building approach. Selected model contains variables that have the most significance. This means that model is treated in a way that new variables are fed to the model one at the time. At each step, each variable that is not already in the model is tested for inclusion in the model performance.

Table 3 Regression parameters for action probabilities and for full closing and opening probabilities

Type	Parameters	Estimate	X^2
Closing (arriving)	a	-7.41	
	b_{Ein}	$10.35*10^{-4}$	3005.04
	B_b	2.17	177.79
Opening (arriving)	a	-1.52	
	b_{Ein}	$-6.54*10^{-4}$	202.87
	B_b	-3.139	2127.15
Closing (intermediate)	a	-8.013	
	b_{Ein}	$8.41*10^{-4}$	4173.2
	B_b	1.270	2416.84
Opening (intermediate)	a	-3.625	
	b_{Ein}	$-2.76*10^{-4}$	155.24
	B_b	-2.683	4600.57
Closing (full)	a	-0.27	
	B_b	-2.23	55.9
	$b_{Egl,hor}$	$0.91*10^{-6}$	4
Opening (full)	a	0.435	
	B_b	1.95	284.7
	$b_{Egl,hor}$	$-2.31*10^{-5}$	458.8

Probability of an opening action on arrival is driven by the state of the blind (*B*) as the influential variable as well as indoor illuminance (E_{in}).When the occupancy variable is fulfilled, the arrival time and state of the shade are determined, then, using logistic distribution equation the model will produce the probability of the action on the arrival. The model that predict actions on arrival is thus (Equations 2 and 3):

$$Logit\left(P_{closing\ arr}\right) = -7.41 + 10.35 * 10^{-4} * E_{in} + 2.17 * B \quad (2)$$
$$Logit\left(P_{opening\ arr}\right) = -1.52 - 6.45 * 10^{-4} * E_{in} - 3.139 * B \quad (3)$$

In case when the model predict that the actions is going to occur, the second step is to determine if that actions could be fully closing or fully opening. Again, the forwarding selection is being used to determine right parameters to conclude a distribution for the probability of full closing and full opening action. The key predictors remain to be $E_{gl,hor}$ and the shade state. Using regression parameters from Table 3 for the logistic regression model, the equation for full actions is as follows:

$$Logit\ (P_{full}) = a + b * E_{gl.hor} + b_b * B \quad (4)$$

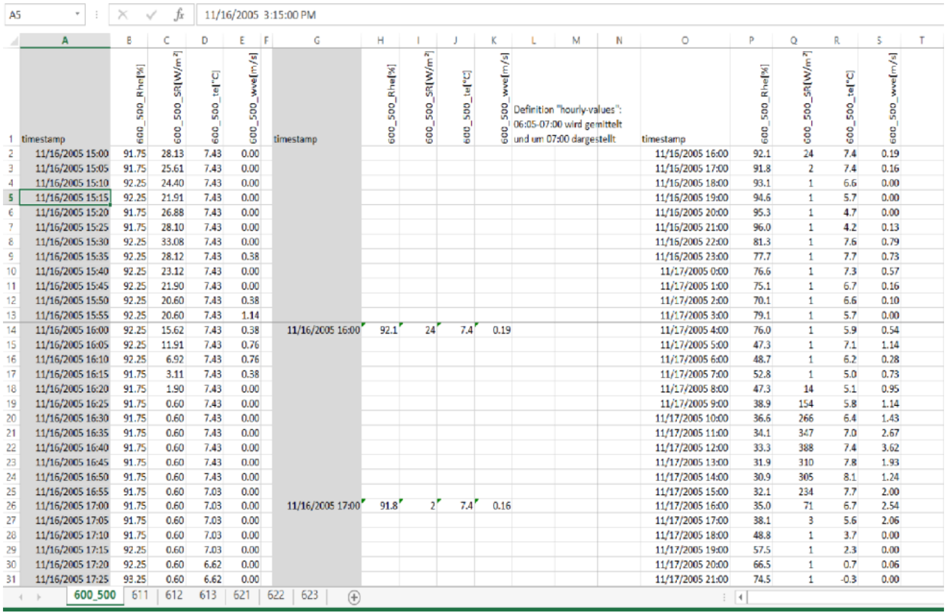
$$Logit\left(P_{full\ closing}\right) = -0.27 + 0.91 * 10^{-6} * E_{gl.hor} - 2.23 * B \quad (5)$$
$$Logit\left(P_{full\ opening}\right) = 0.435 - 2.31 * 10^{-5} * E_{gl.hor} + 1.95 * B \quad (6)$$

If the action is not going to be fully closing or fully opening, the second sub-model is initiated that determines shaded fraction from a relevant distribution. This is determined with a Weibull distribution (Equation 7) with a scale parameter which depends on the initial shaded fraction (λ= exp (-2.294 + 1522 $B_{initial}$)) and a shape parameter (a) of 1.708.

$$f(\Delta B|B_{initial}) = \frac{\alpha}{\lambda}\left(\frac{\Delta B}{\lambda}\right)^{\alpha-1} exp\left(-\left(\frac{\Delta B}{\lambda}\right)^{\alpha}\right) \quad (7)$$

2.5 Implementation of the shade operation model

The dataset included 9-month measurement of interior and exterior parameters as well as shade states in 5-minute intervals Obtained from 6 offices with 10 workstations. To start processing the data, all measurements were put in Excel sheets, separating each office at first and later all the data was divided for each window individually. A sample Excel sheet is shown in Figure 14.



A5 | 11/16/2005 3:15:00 PM

Row	timestamp	600_500_Rhe[%]	600_500_SR[W/m²]	600_500_te[°C]	600_500_wve[m/s]	timestamp	600_500_Rhe[%]	600_500_SR[W/m²]	600_500_te[°C]	600_500_wve[m/s]
2	11/16/2005 15:00	91.75	28.13	7.43	0.00					
3	11/16/2005 15:05	91.75	25.61	7.43	0.00					
4	11/16/2005 15:10	92.25	24.40	7.43	0.00					
5	11/16/2005 15:15	92.25	21.91	7.43	0.00					
6	11/16/2005 15:20	91.75	26.88	7.43	0.00					
7	11/16/2005 15:25	91.75	28.10	7.43	0.00					
8	11/16/2005 15:30	92.25	33.08	7.43	0.00					
9	11/16/2005 15:35	92.25	28.12	7.43	0.38					
10	11/16/2005 15:40	92.25	23.12	7.43	0.00					
11	11/16/2005 15:45	92.25	21.90	7.43	0.00					
12	11/16/2005 15:50	92.25	20.60	7.43	0.38					
13	11/16/2005 15:55	92.25	20.60	7.43	1.14					
14	11/16/2005 16:00	92.25	15.62	7.43	0.38	11/16/2005 16:00	92.1	24	7.4	0.19
15	11/16/2005 16:05	92.25	11.91	7.43	0.76					
16	11/16/2005 16:10	92.25	6.92	7.43	0.76					
17	11/16/2005 16:15	91.75	3.11	7.43	0.38					
18	11/16/2005 16:20	91.75	1.90	7.43	0.00					
19	11/16/2005 16:25	91.75	0.60	7.43	0.00					
20	11/16/2005 16:30	91.75	0.60	7.43	0.00					
21	11/16/2005 16:35	91.75	0.60	7.43	0.00					
22	11/16/2005 16:40	91.75	0.60	7.43	0.00					
23	11/16/2005 16:45	91.75	0.60	7.43	0.00					
24	11/16/2005 16:50	91.75	0.60	7.43	0.00					
25	11/16/2005 16:55	91.75	0.60	7.03	0.00					
26	11/16/2005 17:00	91.75	0.60	7.03	0.00	11/16/2005 17:00	91.8	2	7.4	0.16
27	11/16/2005 17:05	91.75	0.60	7.03	0.00					
28	11/16/2005 17:10	91.75	0.60	7.03	0.00					
29	11/16/2005 17:15	92.25	0.60	7.03	0.00					
30	11/16/2005 17:20	92.25	0.60	6.62	0.00					
31	11/16/2005 17:25	93.25	0.60	6.62	0.00					

Row	Definition "hourly-values": 06:05-07:00 wird gemittelt und um 07:00 dargestellt	timestamp	600_500_Rhe[%]	600_500_SR[W/m²]	600_500_te[°C]	600_500_wve[m/s]
2		11/16/2005 16:00	92.1	24	7.4	0.19
3		11/16/2005 17:00	91.8	2	7.4	0.16
4		11/16/2005 18:00	93.1	1	6.6	0.00
5		11/16/2005 19:00	94.6	1	5.7	0.00
6		11/16/2005 20:00	95.3	1	4.7	0.00
7		11/16/2005 21:00	96.0	1	4.2	0.13
8		11/16/2005 22:00	81.3	1	7.6	0.79
9		11/16/2005 23:00	77.7	1	7.7	0.73
10		11/17/2005 0:00	76.6	1	7.3	0.57
11		11/17/2005 1:00	75.1	1	6.7	0.16
12		11/17/2005 2:00	70.1	1	6.6	0.10
13		11/17/2005 3:00	79.1	1	5.7	0.00
14		11/17/2005 4:00	76.0	1	5.9	0.54
15		11/17/2005 5:00	47.3	1	7.1	1.14
16		11/17/2005 6:00	48.7	1	6.2	0.28
17		11/17/2005 7:00	52.8	1	5.0	0.73
18		11/17/2005 8:00	47.3	14	5.1	0.95
19		11/17/2005 9:00	38.9	154	5.8	1.14
20		11/17/2005 10:00	36.6	266	6.4	1.43
21		11/17/2005 11:00	34.1	347	7.0	2.67
22		11/17/2005 12:00	33.3	388	7.4	3.62
23		11/17/2005 13:00	31.9	310	7.8	1.93
24		11/17/2005 14:00	30.9	305	8.1	1.24
25		11/17/2005 15:00	32.1	234	7.7	2.00
26		11/17/2005 16:00	35.0	71	6.7	2.54
27		11/17/2005 17:00	38.1	3	5.6	2.06
28		11/17/2005 18:00	48.8	1	3.7	0.00
29		11/17/2005 19:00	57.5	1	2.3	0.00
30		11/17/2005 20:00	66.5	1	0.7	0.06
31		11/17/2005 21:00	74.5	1	-0.3	0.00

600_500 | 611 | 612 | 613 | 621 | 622 | 623

Figure 14 Excel sheet screenshot of the measured data

However, not all the parameters that are needed for the model to run are measured in the HB building. One of the essential parameters was outdoor horizontal illuminance, which was derived from an EnergyPlus model. A simple shoebox model was created and with the right weather file for the area the simulation was done in order to get the aforementioned parameter. Figure 15 shows a snapshot of the graphical user interface of the EnergyPlus 8.6.0 application.

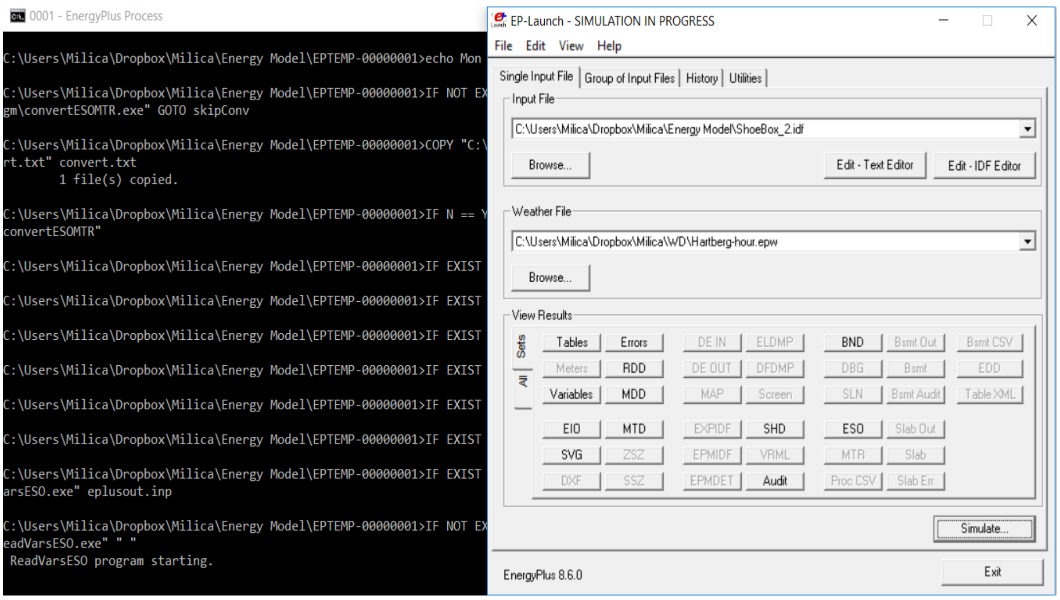


Figure 15 User interface for EnergyPlus simulations

However, the major part of data processing and model implementation was conducted in Matlab. To achieve the study objectives a number of scripts were written, which made it possible to execute and evaluate the model using the new dataset. The resulting indicators gathered from these scripts were later proceeded in Excel to create tables and charts for presentation.

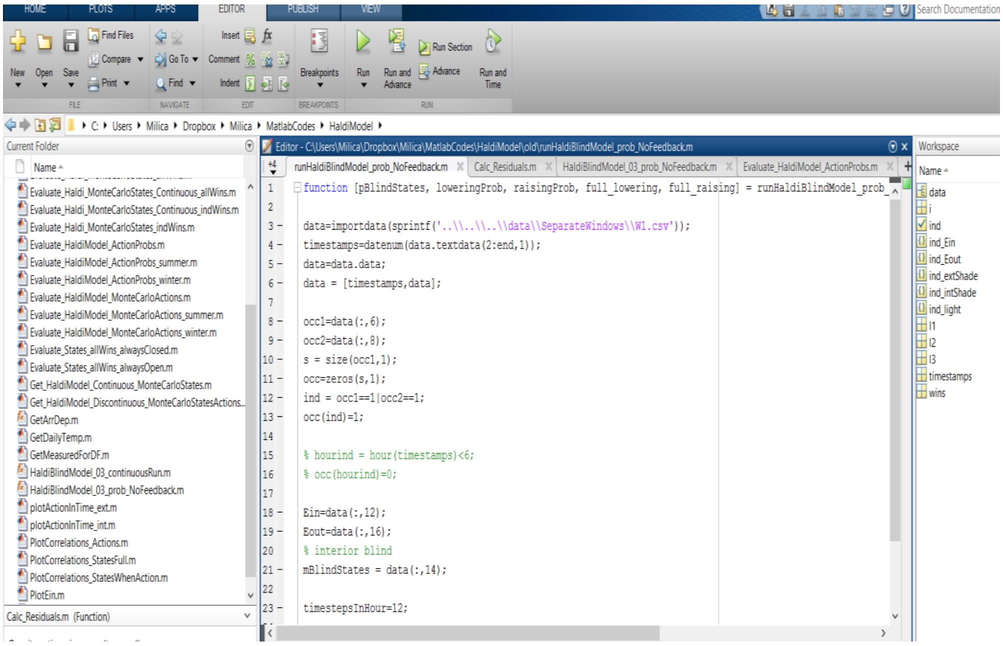


Figure 16 User interface in Matlab

2.6 Model evaluation approaches

Occupant behavior models are intended to predict the occupants' operation of control devices and/or the resulting state of building environmental control systems. In this study, actions refer to the opening/closing of the shades, whereas states refer to the position of the shades.

For this study, the following approaches were adopted to evaluate the predictive potential of the shading operation model in view of occupants' interaction with both interior and exterior shadings:

- Comparing predicted action probabilities with the observed actions;
- Comparing the predicted actions with observed actions;
- Comparing predicted and observed shading states.

It should be noted that the first approach relies on the predicted probabilities of shading operation and thus is not sensitive to multiple runs of the stochastic model. However, the second and third approaches evaluate the predicted shading operation actions and the resulting states which are in principle different in each model run. Therefore, to evaluate the models based on the predicted actions and states, we conducted a 100-run Monte-Carlo simulation of the model.

For the third approach we used continuous and discontinuous runs of the models. These approaches together allow us to gain a better understanding of the model performance despite the fact that the model feedback is not included in the evaluation process.

Thus, the study makes it possible to examine if the model's predictive performance deteriorates substantially when applied to data that were not used in model estimation.

2.6.1 Predicted action probabilities and observed actions

First approach in the evaluation of the model was to compare probabilities of predicted actions with actual actions. This approach was first suggest by Fabi et al. (2015). As mentioned before, the indicators used in this approach are not sensitive to multiple run of the model, which makes the evaluation process much less computationally expensive. The action probabilities are derived from logical regression sub-models in the shade operation model. After obtaining these probabilities, the comparison is being conducted with observed actions, separately for opening and closing. The data is collected in terms of 5 minute intervals over almost 9 months. However, not each interval is considered in for this evaluation, due to the fulfillment of the requirement witch is occupancy. Of course, the evaluation of predicted opening probabilities is conducted only in the intervals in which an opening is possible (that is, the shade is not already fully open). The same treatment applies to the predicted closing probabilities.

2.6.2 Predicted and observed actions

Second approach in this study is to compare predicted and observed actions. This method is based on random process of the stochastic model. Using Monte Carlo method (repeated random sampling to obtain numerical results) with 100 runs, the model predict if an opening or closing action happens or not, which is then compared with the observed actions.

Note that the model first determines if an action happens. When the model determines what action is happening (opening or closing), the next step is to establish the extent of the action (resulting fraction of shading), which necessitates the fallowing evaluation approach.

2.6.3 Predicted and observed states

The third approach involves comparison of the predicted and measured shading states. Similar to evaluation of predicted actions, in this approach the Monte-Carlo method is used. Every run of the model produces different results, thus the 100 runs simulations is conducted to achieve more reliable results. For this approach, two scenarios for model execution were used: continuous model run without feedback and discontinuous model run.

In discontinuous model run (Figure 17) the input are always given to the model from the measured data. This means, that the model is producing the prediction of shading state just for one time interval, and then for the fallowing interval, the inputs are reset based on the measured data. In the continuous model run without feedback (Figure 18), in the first interval the model uses the measured data to obtain first shading state. However, for all the fallowing intervals, it uses previous shading state predicted by model as input. The feedback of the model is disregarded in this approach, which makes the evaluation to some degree inaccurate.

However, it should be noted that without having a highly accurate performance model of the building, which can predict the indoor illuminance resulting from the predicted shade states, it is not possible to include the model feedback in the evaluation procedure. Therefore, the current study aims to provide a more informative analysis of the model performance by combining both discontinues and continuous model runs in the evaluation process.

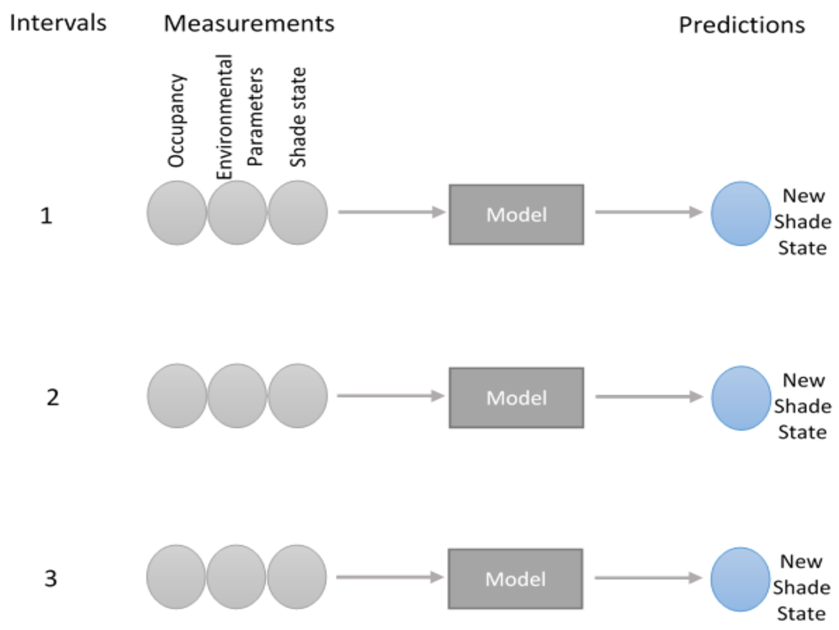


Figure 17 Schematic representation of the discontinuous model run

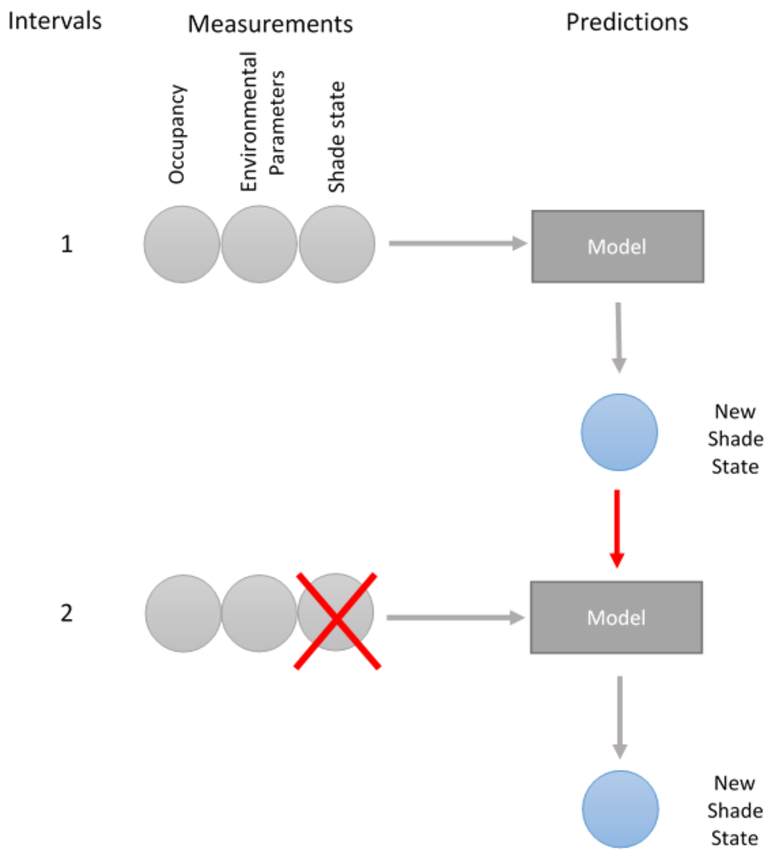


Figure 18 Schematic representation of continuus model run

2.6.4 Model evaluation metrics

Given the three aforementioned model evaluation approaches the following metrics are used to assess the model predictive potential:

- MAR (Mean Absolute Residuals)
- Number of Actions
- Mean shaded fraction
- MBE (Mean Bias Error)
- RMSE (Root Mean Square Error)

Residual of an observed value is the difference between the observed value and the estimated value of the quantity of interest. For the purpose of current study, the residuals are calculated for the differences between the probability of actions and observed actions, whereby the mean absolute residual gives an overall picture with regard to the deviation of the predicated probabilities from the observed actions in the whole monitoring period. Number of actions as an indicator is straight forward metric used to compare the measured action and predicted actions given by the model.

Mean shaded fraction indicates the percentage of the shading averaged throughout the whole monitoring period. Mean bias error refers to the tendency of a measurement process to over- or underestimate the value of a population parameter. In this case, MBE would be the difference between predicted and measured shading state that is expressed in percentage of error.

Root mean square error is a frequently used measure of the magnitude of differences between values (sample and population values) predicted by a model and the values actually observed.

3 RESULTS AND DISCUSSION

3.1 Predicted probabilities and observed actions

Table 4 gives the values of mean absolute residuals of opening and closing probabilities for interior shades. In addition, Table 4 provides the number of measured actions, and the number of intervals, which have been used to calculate the aforementioned metrics for each window. Note that, the number of test intervals for opening and closing is not the same. This results from the available monitored data. For example, 78 opening test intervals for the first window means that there are 78 interval in which the interior shade is partially or fully closed and thus can be opened. Table 5 provides the same results for exterior shades. Note that the NaN values of MARPP appear when there is no applicable interval to calculate the metric. For example, in Table 4, for the window number 6, the number of test intervals for closing actions are 0 and the MARPP values for closing is in turn NaN.

Table 4 Mean absolute residuals of predicted opening and closing probabilities for interior shadings

Window number	Number of test intervals		Number of measured actions		Mean absolute residual of predicted probabilities (MARPP)	
	Opening	Closing	Opening	Closing	Opening	Closing
1	78	9142	6	6	0.053	0.001
2	328	8938	17	17	0.035	0.002
3	9255	402	1	1	0.002	0.003
4	145	8537	2	2	0.016	0.001
5	11670	36	4	4	0.002	0.112
6	11907	0	0	0	0.002	NaN
7	11760	157	11	11	0.003	0.071
8	1	2172	1	1	0.905	0.002
9	113	1891	3	3	0.028	0.003
10	2	7018	2	2	0.997	0.001
11	87	4242	3	3	0.036	0.001
12	0	1377	0	0	NaN	0.005
13	271	1252	8	8	0.028	0.007
14	60	1261	3	3	0.052	0.005
Total	**45677**	**46425**	**61**	**61**	**0.003**	**0.002**

Table 5 Mean absolute residuals of predicted opening and closing probabilities for exterior shadings

Window number	Number of test intervals		Number of measured actions		Mean absolute residual of predicted probabilities (MARPP)	
	Opening	Closing	Opening	Closing	Opening	Closing
1	188	9144	1	1	0.017	0.001
2	204	9189	9	8	0.031	0.001
3	113	9651	3	3	0.034	0.001
4	476	8206	1	2	0.004	0.001
5	71	11701	0	1	0.003	0.001
6	278	11908	1	1	0.010	0.001
7	0	11907	0	0	NaN	0.001
8	1	2172	1	1	0.983	0.002
9	19	1989	0	2	0.058	0.002
10	1426	6884	3	5	0.009	0.002
11	2145	2882	1	2	0.004	0.001
12	174	1209	2	2	0.014	0.008
13	105	1515	1	2	0.014	0.004
14	244	1326	3	3	0.027	0.007
Total	**5444**	**89683**	**26**	**33**	**0.010**	**0.001**

The values of mean absolute residual of predicted probabilities in Table 4 and Table 5 are very low, showing that the model works properly in view of predicting low probabilities of actions. This is in accordance with the observation that the number of actions are very low compared to the total test intervals. However, the extremely low values of the metric do not contribute much to understand the model performance. In other words, the large number of intervals as compared to the number of actions (as given in the Table 4 and Table 5), reduces the sensitivity of the metric to capture the model performance with a fine resolution. Thus, even though the examination of predicted probabilities largely reduces the computational cost of Monte Carlo runs, the current study could not infer a high potential in this approach for evaluation of occupant behavior models.

3.2 Predicted and observed actions

Table 6 gives the measured and predicted opening and closing actions for interior shades. Table 7 presents the same results for the exterior shades. Note that, the number of predicted actions is the mean values of the 100-run Monte-Carlo simulation of the stochastic shade operation model. To better illustrate the predictive performance of the model in different seasons, Figure 19 and Figure 20 show the scatter diagram of the measured and predicted actions during the monitoring period.

Table 6 Number of measured and predicted action of interior shading

Window number	Number of measured actions		Number of predicted actions		Number of actions Relative Error	
	Opening	Closing	Opening	Closing	Opening	Closing
1	6	6	0.1	4.2	-97.8%	-29.7%
2	17	17	0.6	5.1	-96.7%	-70.2%
3	1	1	20.8	0.2	1981.0%	-83.0%
4	2	2	0.3	4.6	-85.5%	131.0%
5	4	4	18.5	0.1	361.3%	-98.8%
6	0	0	20.6	0.0	NaN	NaN
7	11	11	20.1	0.1	82.8%	-99.2%
8	1	1	0.1	1.2	-88.0%	24.0%
9	3	3	0.2	2.2	-92.0%	-28.0%
10	2	2	0.0	3.9	-99.0%	92.5%
11	3	3	0.1	2.3	-95.7%	-25.0%
12	0	0	0.0	7.0	NaN	NaN
13	8	8	0.6	2.5	-93.1%	-68.6%
14	3	3	0.1	3.2	-97.0%	5.3%
Total	**61**	**61**	**82.1**	**36.4**	**34.5%**	**-40.3%**

Table 7 Number of measured and predicted action of exterior shading

Window number	Number of measured actions		Number of predicted actions		Number of actions Relative Error	
	Opening	Closing	Opening	Closing	Opening	Closing
1	1	1	2.2	4.3	115.0%	330.0%
2	9	8	1.2	6.0	-86.3%	-25.4%
3	3	3	0.9	4.2	-70.7%	40.7%
4	1	2	1.1	4.1	13.0%	103.0%
5	0	1	0.3	12.9	NaN	1191.0%
6	1	1	1.7	10.7	74.0%	966.0%
7	0	0	0.0	10.9	NaN	NaN
8	1	1	0.0	1.4	-99.0%	41.0%
9	0	2	0.1	3.0	NaN	51.0%
10	3	5	5.4	5.0	79.3%	-0.8%
11	1	2	7.4	2.2	643.0%	10.0%
12	2	2	0.5	6.4	-76.0%	220.5%
13	1	2	0.5	3.6	-54.0%	77.5%
14	3	3	2.0	3.6	-34.7%	19.3%
Total	**26**	**33**	**23.2**	**78.1**	**-10.6%**	**136.8%**

From Table 6 and Table 7, the observed number of opening and closing actions, both for interior and exterior shades, are not high. However, it is clearly noticeable that the occupants use interior shades more frequently. Specifically, the number of observed interior shade operation actions is double for both opening and closing.

The model predictions in terms of opening and closing actions for interior shade are slightly different than observed actions. While with regard to exterior shade, the opening actions are highly overestimated and closing actions are very close. This can be seen in terms of the relative error, as the indicator of the over- and under-estimation is presented in percentage (positive and negative). When compared for all the interior or exterior shades, predicted action for interior shades are overestimated for closing by 34.5% and opening by 40.3%. However, for the exterior shades, predicted opening actions are highly overestimated, resulting in relative error of 136.8%. When looking individual windows, either interior or exterior shade, the relative errors can be very high. In some cases the relative is positive whereas in other cases it is negative, resulting in mean value that is explained before.

It should be noted that, for the purpose of the current study, the shade operation model has been used in the same manner for the interior and exterior shades, without considering the interrelations between the usages of different shades on the same window.

However, when looking at the model predictive performance in different time of the year (see Figure 19 and Figure 20), it can be seen the model largely overestimates the opening and closing actions in the cold season. This clearly indicates that the model (with mainly one independent variable, namely indoor illuminance) cannot capture different patterns of occupant interactions with shade in hot and cold seasons. This failure in replicating the occupants' operation of shades in winter is much more noticeable in case of exterior shades.

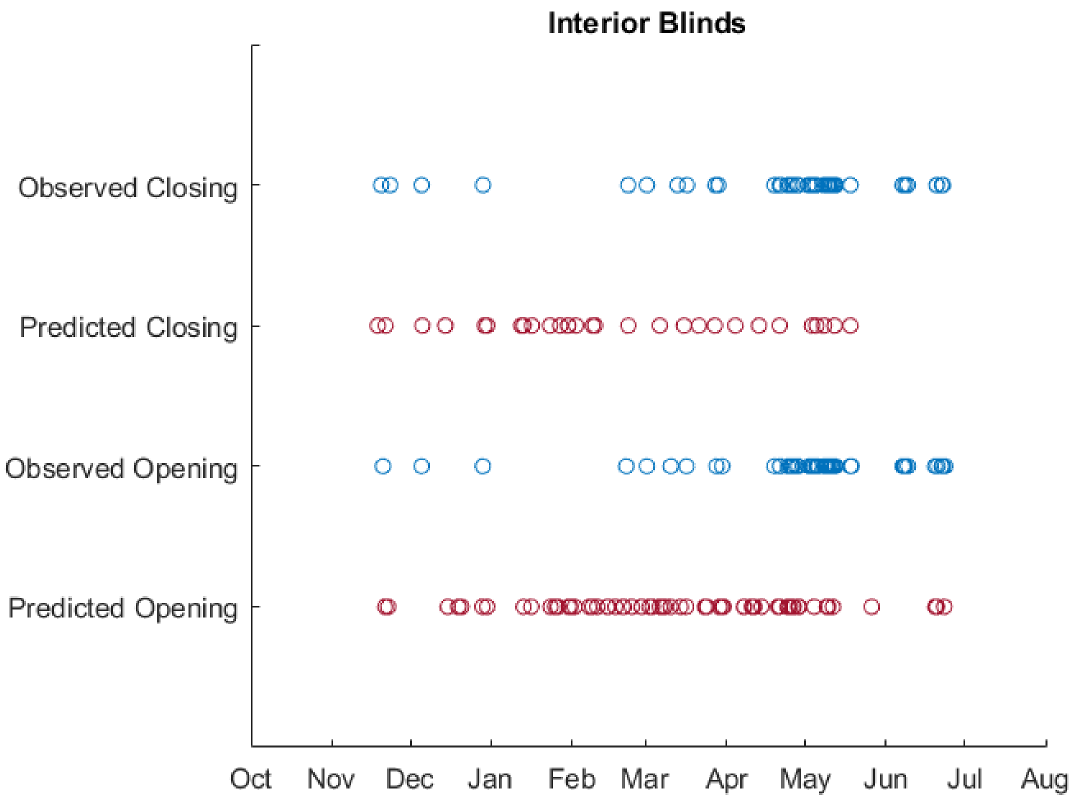


Figure 19 Scatter diagram of observed and predicted action of interior shading

Figure 20 Scatter diagram of observed and predicted action of exterior shading

3.3 Predicted and observed states

As explained in section 2.6.3, given the fact that it was not possible to include the model feedback in model evaluation, we adopted two approaches to capture the model performance in predicting state of the shades.

3.3.1 Discontinuous model run

Table 8 presents the evaluation metrics for interior shades' state predictions obtained from discontinuous model run. Table 9 provides the same evaluation metrics for the exterior shades.

Table 8 Evaluation metrics for interior shades' state predictions obtained from discontinuous model run

Window number	Mean shaded fraction		MBE	RMSE
	Measured	Predicted		
1	0.01	0.01	0.000	0.03
2	0.04	0.04	0.000	0.05
3	0.96	0.96	-0.002	0.04
4	0.02	0.02	0.000	0.02
5	1.00	1.00	-0.001	0.04
6	1.00	1.00	-0.001	0.04
7	0.99	0.99	-0.001	0.05
8	0.00	0.00	0.000	0.01
9	0.05	0.05	0.000	0.04
10	0.00	0.00	0.000	0.01
11	0.02	0.02	0.000	0.04
12	0.00	0.00	0.001	0.02
13	0.07	0.07	-0.001	0.05
14	0.01	0.01	0.000	0.04
Total	**0.42**	**0.42**	**0.000**	**0.04**

Table 9 Evaluation metrics for exterior shades' state predictions obtained from discontinuous model run

Window number	Mean shaded fraction		MBE	RMSE
	Measured	Predicted		
1	0.01	0.01	0.000	0.01
2	0.03	0.03	0.000	0.02
3	0.01	0.01	0.000	0.02
4	0.05	0.05	0.000	0.02
5	0.00	0.01	0.001	0.02
6	0.01	0.01	0.000	0.02
7	0.00	0.00	0.000	0.02
8	0.00	0.00	0.000	0.01
9	0.01	0.01	0.000	0.01
10	0.16	0.16	0.000	0.03
11	0.43	0.43	-0.001	0.03
12	0.04	0.04	0.000	0.03
13	0.02	0.02	0.000	0.02
14	0.03	0.04	0.000	0.02
Total	**0.04**	**0.04**	**0.000**	**0.02**

From Table 8 and Table 9, it can be seen that evaluation of model performance in predicting the shade states using a discontinuous run of the model cannot properly capture the model performance. Even though the error indicators show very low values (in terms of overall shaded fraction or interval by interval comparisons), arguably it cannot be interpreted as superior performance of the model. Because, it should be considered that in this evaluation approach, the model is provided with correct initial shade state at each interval to predict the new state of the shade (see Figure 17). This means that, considering the low probabilities of actions, in the majority of time intervals the model just returns the initial state as output, which given the low number observed actions matches the measured states in the majority of cases. Besides, if the model predicts the shade state wrongly in a time interval, the wrong prediction will not be kept for the following interval (which is the way such models are intended to be used in building performance simulation models).

To put the model performance (captured in a discontinuous run) in perspective, in Table 10 and Table 11, the evaluation indicators are also given for a pseudo model that never predicts an action. That is, the model always return the initial state of the shade as the prediction for the next state of the shade. From the results, it can be seen that the no-action model performs even better that the studied stochastic shaded model. Therefore, it can be argued that the current approach (discontinuous model run to evaluate state predictions) is not very helpful to evaluate the model performance.

Table 10 Comparison of the model performance with measured and no-Action model using disconnected intervals for interior shades

Shading states source	Mean shaded fraction	MBE	RMSE
Measured	42.2%	0.00%	0.0%
Stochastic shading model	42.1%	-0.05%	3.9%
No-Action model	42.2%	0.00%	2.8%

Table 11 Comparison of the model performance with measured and no-Action model using disconnected intevals for exterior shades

Shading states source	Mean shaded fraction	MBE	RMSE
Measured	4.3%	0.00%	0.0%
Stochastic shading model	4.4%	0.02%	2.2%
No-Action model	4.3%	0.00%	1.1%

3.3.2 Continuous model run

To better capture the model performance in predicting shade states, Table 12 and Table 13 present the evaluation metrics for state predictions – for interior and exterior shades respectively – obtained from a continuous run of the shade operation model. Note that, firstly, in continues model run, the model's feedback is disregarded. Secondly, all the evaluation indicators are mean values of a 100-run Monte Carlo simulation of the shade operation model.

From the results, in the continuous model run, the model is not providing a satisfactory prediction of the shade states as observed during the measured period. For example in case of interior shade, the model largely underestimate the overall use of shade. Also in view of interval by interval agreement between predictions and measurements, the mean bias error is showing the underestimation of the model by 27.9% and RMSE shows an average interval error magnitude of 64%. Note that, in this approach, the model is getting the initial input from observed data to make a prediction for the shading state (see Figure 18). However, that prediction is becoming the initial input for the next interval, and thus when a wrong prediction happens, the model is carrying that state until the next prediction. This can explain the differences between the results obtained from the continuous and discontinuous model runs. However, the shortcoming of the continuous model run in this study is that the model feedback (i.e., the impact of predicted shade state on the indoor illuminance as model input) is not included. Therefore, in a number of intervals the measurements may not be in accordance with predicted shade states. In other words, when the prediction happens, for example a closing action, the indoor environmental parameters would change (illuminance values would become smaller) but the model would not have this input for the next interval.

Table 12 Evaluation metrics for interior shades' states obtained from continuous model run

Window number	Mean shaded fraction		MBE	RMSE
	Measured	Predicted		
1	0.01	0.11	0.098	0.29
2	0.04	0.15	0.117	0.39
3	0.96	0.08	-0.875	0.93
4	0.02	0.09	0.073	0.30
5	1.00	0.24	-0.761	0.87
6	1.00	0.18	-0.821	0.90
7	0.99	0.18	-0.810	0.90
8	0.00	0.08	0.082	0.18
9	0.05	0.10	0.049	0.31
10	0.00	0.11	0.110	0.28
11	0.02	0.09	0.071	0.28
12	0.00	0.18	0.178	0.35
13	0.07	0.13	0.056	0.33
14	0.01	0.17	0.152	0.32
Total	**0.42**	**0.14**	**-0.279**	**0.64**

Table 13 Evaluation metrics for extrioir shades' states obtained from continuous model run

Window number	Mean shaded fraction		MBE	RMSE
	Measured	Predicted		
1	0.01	0.10	0.097	0.29
2	0.03	0.14	0.110	0.36
3	0.01	0.09	0.082	0.27
4	0.05	0.10	0.043	0.36
5	0.00	0.22	0.214	0.45
6	0.01	0.18	0.165	0.40
7	0.00	0.18	0.177	0.40
8	0.00	0.05	0.046	0.13
9	0.01	0.11	0.101	0.28
10	0.16	0.12	-0.045	0.44
11	0.43	0.10	-0.332	0.65
12	0.04	0.16	0.116	0.36
13	0.02	0.15	0.135	0.32
14	0.03	0.13	0.091	0.28
Total	**0.04**	**0.14**	**0.097**	**0.40**

3.4 The model's overall predictive performance

Figure 21 shows the frequency of actions based on observed and predicted actions. It is noticeable that, based on observations, the use of interior shading is much frequent that can be interpreted as the occupants had preferences toward internal shades - drapes. In this regard, the model largely underestimates the operation of interior shade. However, in case of the exterior shade with closing actions, the model predicted that the actions should happen much more often than what was measured. Besides, as discussed before, the model predictions differ from the observed actions in terms of timely distribution, where as opposed to the observations, the majority of these actions are predicted to happen in the cold period (Figure 20).

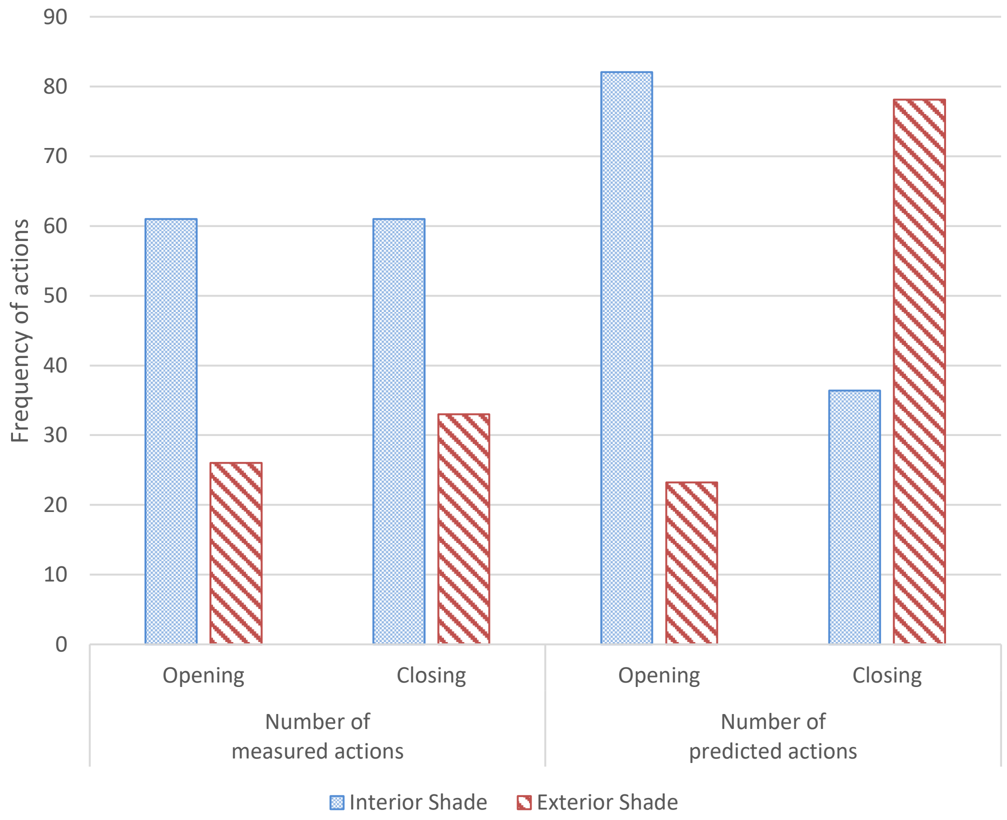


Figure 21 Frequency of actions from observed and predicted data

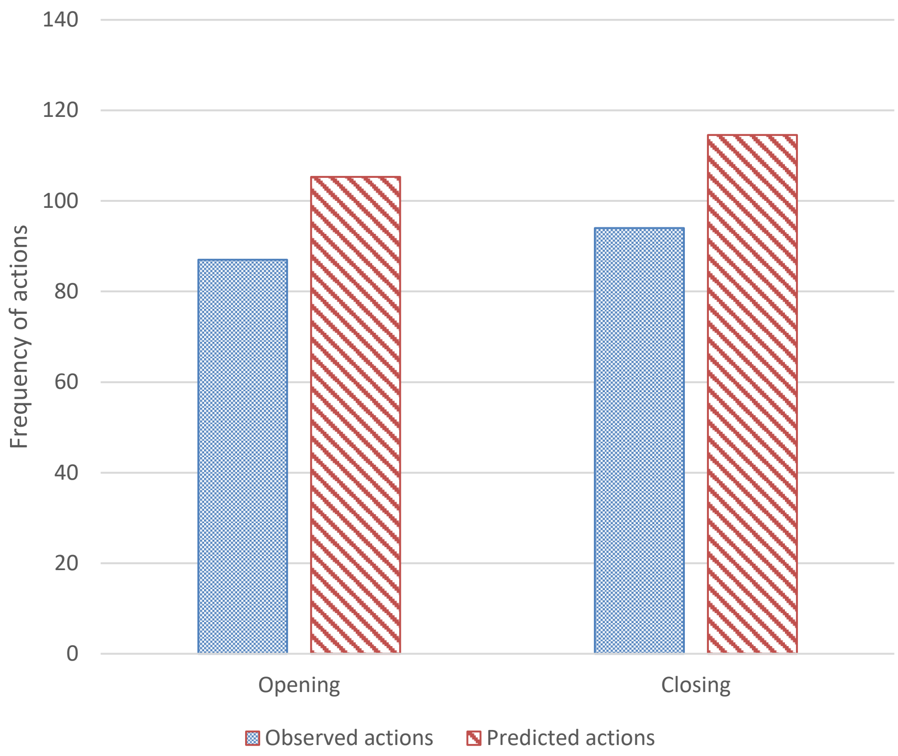


Figure 22 Total frequency of observed and predicted actions

Table 14 gives the total number of shade operations for both interior and exterior shades, which shows an overestimation of 21% for opening and 21.9% for closing actions. Figure 22 shows the total number of actions (interior and exterior combined). The overestimation of the model performance in predicting actions is clearly noticeable in this figure.

Table 14 Relative error of the model performance in predicting actions

Sum of measured actions		**Sum of predicted actions**		**Relative Error of model performance**	
Opening	Closing	Opening	Closing	Opening	Closing
87	94	105.3	114.55	21.03%	21.86%

To normalize the number of actions based on the time intervals, during which the action is possible, Figure 23 shows the hourly rate of observed and measured actions for interior and exterior shades. From Figure 23, it can be seen that the model is overestimating the openings of the interior shading while underestimates openings of the exterior shadings. However, rate of opening actions of exterior shades are much more frequent comparing to all other actions.

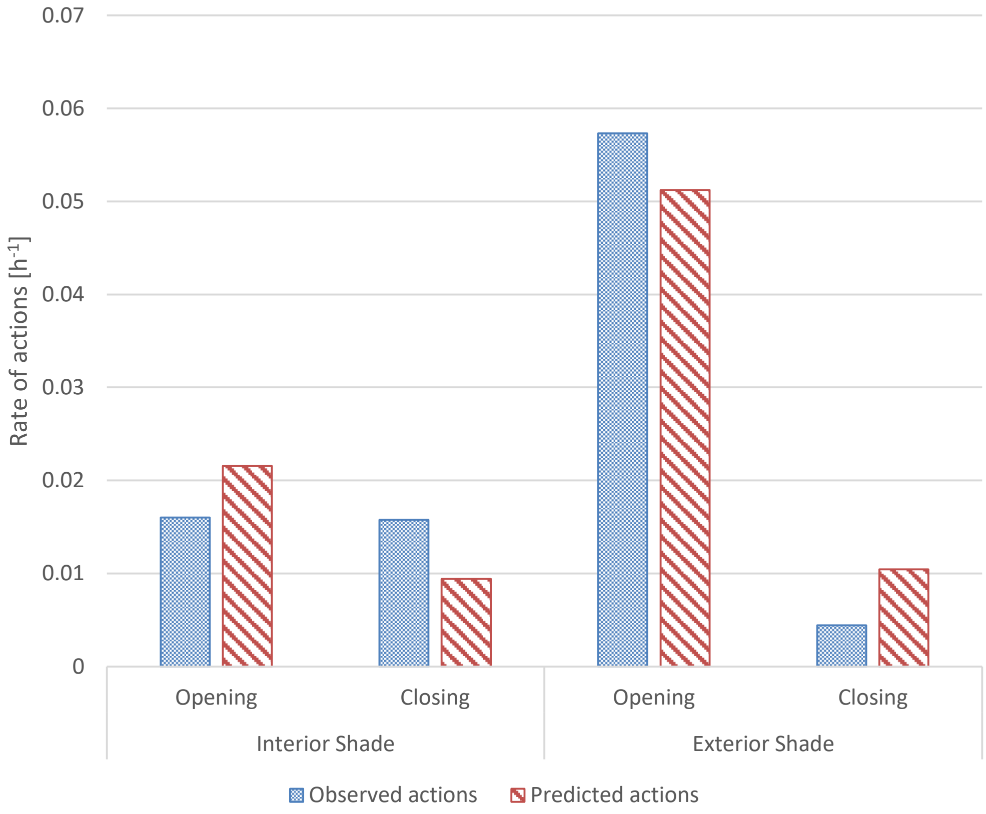


Figure 23 Rate of the observed and predicted actions

Table 15 and Table 16 summarize the obtained results in terms of the observed and predicted states of shades (in the continuous model run) for the interior and exterior shades respectively.

Table 15 Overall evaluation of predicted states for the interior shades obtained from continuous model run

Shading operation model	Mean shaded fraction	MBE	RMSE
Measured	42.0%	0.0%	0.0%
Stochastic model	14.3%	-27.9%	64.3%

Table 16 Overall evaluation of predicted states for the exterior shades obtained from continuous model run

Shading operation model	Mean shaded fraction	MBE	RMSE
Measured	4.0%	0.0%	0.0%
Stochastic model	14.0%	9.7%	40.3%

As it can be seen in Table 15 and Table 16, the studied stochastic model largely underestimates the use of interior shades while it overestimates deployment of the exterior shade. This can be seen both in terms of the overall indicator (mean shaded fraction) and the indicators which aggregate the interval errors (MBE and RMSE). While the results in general do not show a satisfactory performance of the model, they also outline the need for distinct treatment of different types of shades in building. In a broader perspective, the claimed general applicability of developed occupant behavior models may be undermined only due to variations in the type pf control devices.

4 CONCLUSION

Based on the exploration of the shade operation model's predictive performance through different evaluation approaches the following concluding remarks can be mentioned:

- Occupant behavior models developed based on limited number of buildings may not perform satisfactory in new settings. Without more extensive external validation studies the general applicability of such model should not be claimed.
- Different type of shades need different models / coefficients.
- Existing models may be not reliable in specific seasons.
- Without inclusion of models' feedback, occupant behavior models cannot be fully evaluated.

In addition, most importantly, the study concludes that while the probabilistic occupant behavior models can, in principle, enhance the building performance simulation efforts, more straightforward approaches for representation of occupants in building models are needed. That is, from the author's view, without simply defined and easily verifiable occupant behavior models – no matter stochastic or non-stochastic – one cannot promote the use of building performance simulation tools.

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