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Including Occupant Behavior in Building Simulation: Comparison of a Deterministic vs. a Stochastic Approach

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ABSTRACT

Data capture and analysis are transforming entire industries, enabling novel solutions developed from a numeric evaluation of real-world phenomena. This generally relies on gathering data on physical conditions and users to create accurate, predictive models and provide customized solutions. Increasingly, data-driven approaches are also becoming a part of architectural design, with the goal of creating user-centric and sustainable buildings. However, while simulation software can accurately model deterministic physical effects, it is still difficult to incorporate stochastic effects related to human factors. This paper analyses one aspect of occupant behavior – window operation – to give designers an intuition of the impact of occupant behavior and associated modelling approaches on building performance. To this end, behavioral patterns observed in a previous field study were incorporated into a dynamic energy simulation and compared to a deterministically modelled baseline. While the stochastic models appear to better capture the dynamic and probabilistic nature of occupants' actions, the present study highlights the extent to which the assumption with regard to occupant behavior can influence the simulation-assisted performance based design process. The paper also makes suggestions as to how to interpret such simulation results in a way that quantifies the intrinsic uncertainty in stochastic models. We argue that increased data capture and analysis of building inhabitants could lead to a better understanding of their behavior, thereby affecting the decision-making process in favor of a more sustainable and responsive architecture.

Author Keywords

Occupant behavior; EnergyPlus; window operation model; dynamic; stochastic; Markov chain; logistic regression; thermal comfort.

1 INTRODUCTION

Many industries are now relying on gathering user data to create predictive models and provide tailored products. There are several indicators of architecture also becoming an increasingly data-driven field: performance based contracts holding designers accountable for whether their buildings perform in the real world as on paper; green building certifications requiring post-occupancy evaluations (POE); smart building concepts of capturing occupant data to auto-adjust building systems in real-time. In fact, it can be argued that there is a rising cultural expectation of customizable and responsive systems, prompting architects to consider incorporating data-driven design approaches into architectural practice.

Computational design has enabled architects to use simulation software to model various performance aspects of proposed building designs, for instance in respect to their thermal characteristics and structural rigidity. While these applications facilitate modelling deterministic physical effects with largely satisfactory accuracy, the predominant metrics for which architects seek to optimize their designs often relate to how the future occupants will use and perceive a space. Anticipating such phenomena is more challenging since they are intrinsically stochastic and multivariate. For example, modelling occupants' interactions with building control devices (such as windows, shades, etc.) generally involves extracting statistical models from data obtained in field studies. These are then analyzed to find a link between environmental parameters and the probability of control devices being operated at any given time. Inclusion of such probabilistic models into performance-based design process yields new opportunities and threats toward creation of occupant-centric buildings, which will require systematic studies in this emerging field of research in the building industry.

2 OBJECTIVE

This paper analyses a single aspect of occupant behavior, namely window opening behavior. Many years of comfort research have demonstrated the advantages of natural ventilation for sustainable building concepts and human comfort [7]. Natural ventilation can have large impacts on the performance of buildings and the comfort of its inhabitants [8]. However, providing occupants with adaptive environmental controls creates uncertainty of whether they will be used efficiently. Traditionally, energy simulation software is used to model human behavior deterministically, e.g. assuming that windows are opened at a specific predetermined indoor temperature. Such over-simplifications of occupant behavior have often been identified as a cause for the considerable discrepancies frequently observed between building simulation and built reality [4, 9]. Being able to more accurately model human behavior in buildings would therefore not only help architects design more sustainable and user-centric spaces [1], but also make physical simulations more accurate. Several recent field studies have therefore analyzed occupant behavior in terms of adaptive control behavior to inform energy models [3, 5, 9].

In this context, this paper aims to apply a data-driven stochastic model of window operation into early stage building simulations; to give designers an intuition of the effect that occupants can have on the performance of buildings, as well as to describe methods of interpreting the intrinsically uncertain results from predictions of stochastic behavior.

3 METHODS

3.1 Field Data and Statistical Models

The model used for the following simulations was obtained from [11], who conducted a one-year field study in a naturally ventilated office space in Vienna, Austria. The occupants' presence, state of windows and several environmental parameters (including indoor and outdoor air temperature) were monitored on a continuous basis. A logistic regression model was fit to the field data:

$$P = \frac{\exp(\beta_0 + \beta_1\theta_{in} + \beta_2\theta_{out} + \beta_3\theta_{in}\theta_{out})}{1 + \exp(\beta_0 + \beta_1\theta_{in} + \beta_2\theta_{out} + \beta_3\theta_{in}\theta_{out})}$$

in which P is the probability of opening or closing a window, θ_{in} and θ_{out} are indoor and outdoor temperature respectively, and β_0 to β_3 are regression coefficients. These modeling techniques have been widely used in the studies pertaining to occupant behavior modeling [e.g., 3,7,11]. For the current study, the authors used the models developed in [10], which also analyzed inter-occupant diversity by obtaining regression coefficients for each occupant in the field study separately (Table 1). To develop an intuition for the range of possible behavioral patterns and their effects on building performance, we used a best-worst-case approach by running the model for the most 'active' and 'passive' behaviors found in the field study (Figure 1). As for the validity of these models, the aforementioned study demonstrates that the models provide a better representation of occupants' interactions with windows in a free-running office building in Viennese climate [10].

3.2 Model Parameters and Implementation

We used the Rhino/Grasshopper architectural software platform to generate the geometry, set the simulation parameters, trigger the simulation and visualize the results. The simulations were run with EnergyPlus, using the Ladybug/Honeybee plugins for Grasshopper as an interface (figure 2). Dynamically changing window states according to current environmental conditions at each time step required inputting custom EnergyPlus Runtime Language (ERL) code; in each EnergyPlus simulation timestep, sensor objects record the occupancy, θ_{in}, θ_{out} and current window states; the probability of the window opening in the next timestep is then calculated using the logit function with the appropriate coefficients and variables. The next state is determined via Inverse Transform Sampling Method, involving a comparison of the resulting probability P with random numbers. Comfort temperatures θ_{comf} were calculated using Ladybug's implementation of the Adaptive Thermal Comfort model from ASHRAE 55 [2] and compared to the simulated indoor temperatures.

Table 1. Regression coefficients from [11].

Action	Variable	Passive	Aggregate	Active
Opening	Intercept	-10.6882	-22.4190	-10.4233
	θ_{in}	0.2187	0.8031	0.0905
	θ_{in}	0.2100	0.3130	0.2047
	Interaction	-0.0052	-22.4190	-0.0034
Closing	Intercept	23.9665	16.6416	7.9830
	θ_{in}	-1.0969	-0.7013	-0.4323
	θ_{in}	-0.9172	-0.5011	-0.3756
	Interaction	0.0376	0.0186	0.0144

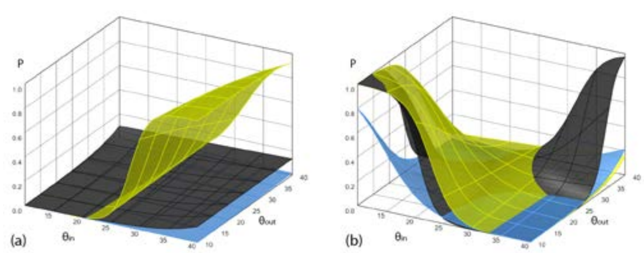

Figure 1. Probability (P) of opening (a) and closing (b) a window based on indoor (θin) and outdoor (θout) air temperature, for average (gray), 'active' (yellow) and 'passive' (blue) occupants.

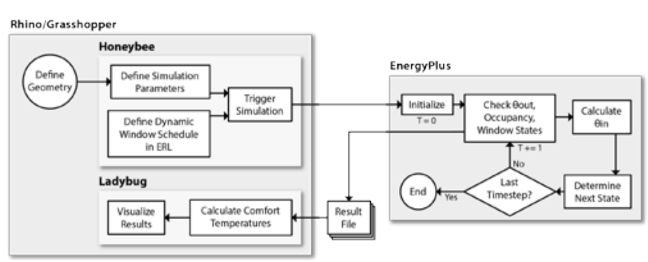

Figure 2. Workflow.

To focus on the implication of occupant behavior models for the early design state simulation based explorations, we did not attempt to remodel the office space from the field study. Instead, a single rectangular naturally ventilated office space with the dimensions 7×10×4m (width×length×height) was chosen for the climate of Vienna, Austria, from which the field study data stems. The north-south oriented room had a 30% glazing portion in the north and south facades. The office space was simulated to be occupied every day between 9am and 5pm. Other schedules and constructions were obtained from the "Closed Office" zone program defaults. Changes of window states were allowed only during office hours; open window states at 5pm therefore led to night ventilation. We adopted a simplified approach in representing the social context in the multi-occupant office, in that cross-ventilation was chosen for the entire simulation. That is, an open window state signifies that both windows were open. θ_{in} values were calculated for an entire year with hourly resolution for 4 window operation models:

1. Deterministic (windows were opened when θ_{in} > 24 °C);
2. Determined by logit function for aggregated field results;
3. Determined by logit function for 'active' user;
4. Determined by logit function for 'passive' user.

4 RESULTS

Each simulation was run via Honeybee in a sub-hourly resolution for an entire year (8760 hours). For the cases 2-4, the simulation was conducted for 100 times to obtain the distribution of results. Figure 3 shows an excerpt of the outputs documented in simulation 2 during a summer week. In the visualized timeframe, θ_{in} was continuously higher than θ_{out}. Opening a window therefore had a cooling effect; longer periods of window openings, especially during night ventilation, caused θ_{in} to approach θ_{out}. The heat maps in figures 4-7 visualize window states, as well as the extent to which θ_{in} differed from θ_{comf} (obtained from the adaptive thermal comfort model) for each of the simulations. These allow to visually detect that window openings were much more common in the deterministic model, which reacted immediately to rising temperatures with window operations. The graphs showing the deviation from θ_{comf} illustrate that for the larger part of the year, θ_{in} was below θ_{comf}. Higher θ_{in} values, and therefore increased thermal discomfort, was observed to be shifted towards the afternoon hours. We used three metrics to summarize these effects (Table 2), taking only into account the model results during office hours: the percentage of hours with open windows, the percentage of hours where θ_{in} was higher than θ_{comf}, and the average

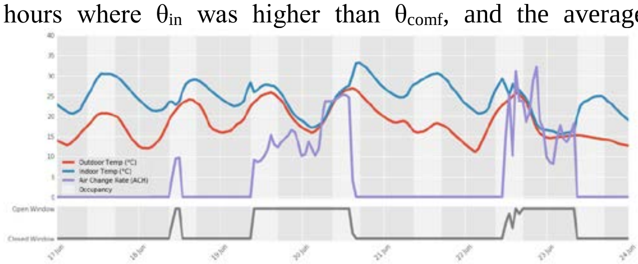

Figure 3. Excerpt from the results of simulation 2.

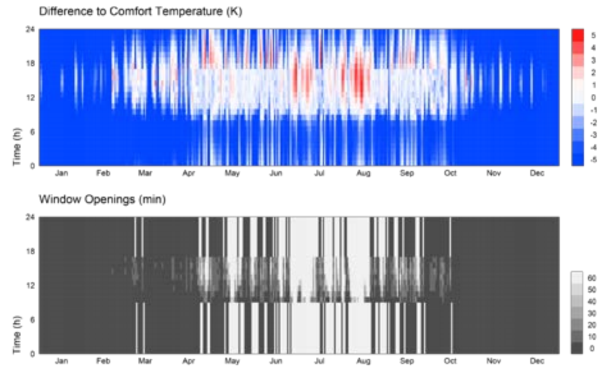

Figure 4. Results from simulation 1 (deterministic model).

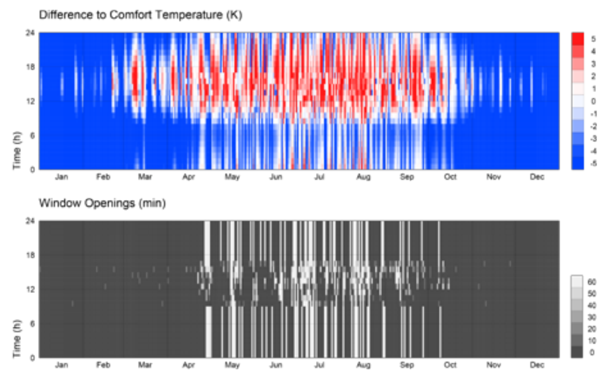

Figure 5. Results from simulation 2 (aggregated occupants).

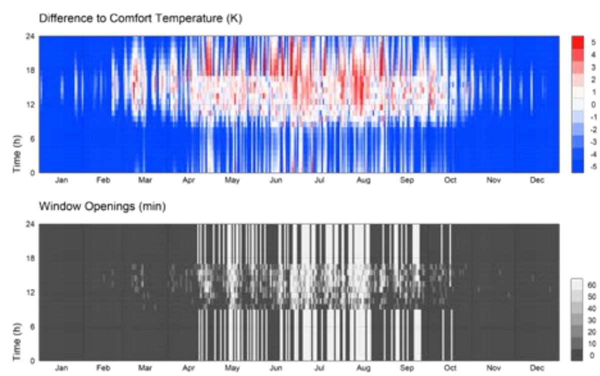

Figure 6. Results from simulation 3 ('active' occupant).

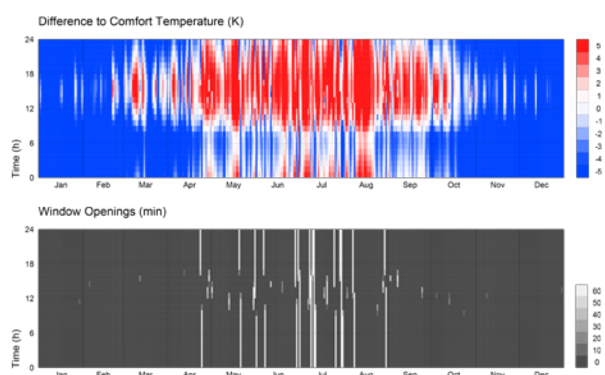

Figure 7. Results from simulation 4 ('passive' occupant).

deviation of θ_{in} from θ_{comf} when θ_{in} was higher than θ_{comf}. Simulations with higher proportions of window openings incurred lower occurrences of thermal discomfort due to overheating. The deterministic model over-predicted comfort within the space even as compared with the 'active' stochastic model. There were also large inter-occupancy differences when using the logistic regression models; the 'passive' model predicted an average 4.55 K above θ_{comf} in comparison to only 1.7 K for the 'active' model.

Table 2. Simulation results summarized for office hours.

	Description	% hours with open windows	% hours when $\theta_{in} > \theta_{comf}$	Average $\Delta\theta$ when $\theta_{in} > \theta_{comf}$
1	Deterministic	11%	37%	1.3 [K]
2	Logit (aggregate)	14.25±1.23	43.26 ± 0.44	3.09±0.01
3	Logit (passive)	3.43±0.66	50.04±0.27	4.55±0.01
4	Logit (active)	19.28±0.63	38.26±0.33	1.72±0.0

5 CONCLUSION

The motivation for writing this paper was to address the trend towards data-driven design and the increasing expectations of occupants and clients towards user-centeredness. As an example, we focused on a single aspect of occupant behavior – namely window opening patterns – and how to include this into the design process. We implemented a model derived from field data into a common architectural flexible modelling software.

The results from our case study showed a large deviation between the common way in which architects simulate indoor thermal comfort in early design, and the results from statistical models based on field data. While the stochastic models can in principle better capture the dynamic nature of occupants' actions, the study showed that a standard model can over-predict comfort. While the current study lacks verification and therefore cannot show which method is more accurate, the observed deviations show that different design solutions may have been driven from the parametric studies. This necessitates further studies toward finding fit-for-purpose occupant behavior models for different simulation-based building design enquiries. In addition, when incorporating field data, we found that inter-occupant behavioral diversity had a large impact on simulation results.

Simulations of the kind reported in this paper are proposed to support the choice between free-running, mixed-mode and air-conditioned options for a given design, as well as to determine an appropriate number of operable windows, which can affect the segmentation of the façade as well as the configuration of indoor spaces to make operable windows accessible. Our case study supports the notion that higher volumes of data collection in architecture are useful to foster new insights on occupants and to incorporate human factors into the computational design process. There still exists only limited field study data on occupant behavior, with observations varying strongly, suggesting that there are many factors influencing behavior. This investigation was limited in that it only attempted to predict window operation, and only did so using temperature as a driving variable. Simulating energy consumption and comfort reliably requires inputting many parameters that are usually not known in early design. Confidence in the results must therefore be managed, and the analysis geared more towards a qualitative understanding of the range of possible outcomes, rather than a primary driver in decision-making.

Moreover, as the existing occupant behavior models are mainly derived from limited data sets, they must be subjected to cross-validation studies in different settings [6]. Analyzing results obtained from such models requires caution and skepticism. Rather than expecting model outputs to dictate design materialization, they need to be evaluated critically and in combination with other design considerations.

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