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The evaluation of stochastic occupant behavior models from an application-oriented perspective: Using the lighting behavior model as a case study

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ABSTRACT

Numerous occupant behavior models, typically stochastic ones, have been built to quantify the effect of occupants on building energy simulation, which however are supposed to go through a rigorous validation, or evaluation process to claim that they are qualified to be used in the application. Current contributions relevant with occupant behavior modeling in literature have been resorting to statistical metrics rather than those orienting on their application, causing the disputation in interpreting the accuracy of the occupant behavior models when they are actually used in simulation. Furthermore, the stochasticity of occupant behavior models necessitates statistical evaluation of the model accuracy, instead of the comparison between actual data and a single-run simulated data. This paper proposes a methodological framework for model evaluation from an application-oriented perspective, with lighting behavior as a case study. The metrics for evaluating lighting behavior models are identified according to different application scenarios, while the comparison between the measurement and simulation is done by introducing the statistical hypothesis testing. Analogous analyses on other behaviors can be conducted in the future, which altogether would foster more rigor and application significance in occupant behavior model evaluation.

1. Introduction

1.1. Background

Occupant behavior is now recognized as a vital contributor to building energy consumption, which draws much attention in building performance simulation [1,16,29,43] as well as energy conservation [2,7,56,57,64]. Various occupant behavior models have been built [22,24,47,49,61] and integrated into current building simulation programs [3,13,18,28,34,69] to quantify the effect of occupant behavior in building energy use.

The simulation results with occupant behavior models integrated in the simulation program depends highly on the validity of the proposed occupant behavior model [39]. Since occupant behavior models often feature stochasticity [10,14,27] as well as the interaction with the indoor and outdoor environment [46,65,67], the evaluation of the model requires a new perspective compared with traditional methods on building simulation models where deterministic approaches were adopted [19,58,59].

1.2. Validation of models

It is important to distinguish whether the model and its results are correct or not, which leads to the importance of the validation and evaluation of the models [52]. When it comes to objective validation, statistical test [44] and confidence intervals usually are introduced, for example, amination, degenerate tests, and so on [5].

Guo [23] proposes fuzzy DEA model to conduct validation. DEA (data envelopment analysis) is a non-parametric technique for measuring and evaluating the relative efficiencies of a set of entities with common crisp inputs and outputs. Moriasi [45] summarizes recommended model evaluation techniques (statistical and graphical), including Nash-Sutcliffe efficiency [21], percent bias (PBIAS), ratio of the root mean square error and the standard deviation of measured data (RSR). The models can be judged as satisfactory if those values are at specific range. As for human behavior model, the emphasis of prediction validation lies on pattern prediction (periods, phase lags, …) rather than point prediction (event). This is a logical result of orientation of

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system dynamic models [6]. The validation includes model structure, structure-oriented behavior and the last, behavior pattern. Steiger [54] discusses a statistical estimation. After correction, RMS is proposed to react as an index. Foss negates the Mean Magnitude of Relative Error (MMRE), which is used to assess the performance of competing software prediction models, to help select the best model [20]. As for mathematical models, Tedeschi makes a complete review and summary [60]. The techniques for model evaluation varies. The first one is analysis of linear regression. The coefficient of determination and MSE are all used to validate. The second technique is analysis of fitting errors, including deviations, extreme points and influential points. The third one is concordance correlation coefficient, to decide whether the model-predicted values are precise and accurate. The fourth one, there are also diverse evaluation measurements, including mean bias, mean absolute error, resistant coefficient of determination, modeling efficiency and so on. What's more, mean square error of prediction can be used to compare accuracy among different models. Besides parametric methods, there is also non-parametric analysis, like Spearman correlation, Kendall's coefficient and balance analysis.

Current occupant behavior models have had attempts in evaluating themselves, as could be seen from the literature [35]. For instance, Andersen listed an array of explanatory variables that window opening and closing could depend on, and introduced the Akaike information criterion (AIC) for selection of variables in the regression model, after which no further evaluation of the model was conducted [4]. Haldi and Robinson [25] compared four indices, namely discrimination, overall prediction, dynamics and aggregated results, among the measured data and different window opening and closing models. The stochasticity of window operation models was taken into account by 20 repeated simulations. Herkel [26] converted the simulated window state data into the mean percentage of open windows during a day and compared them with measured ones to validate the proposed window operation model.

In general, the current approach on the evaluation of stochastic occupant behavior models bears some deficiencies. (1) Some occupant behavior models were not fully evaluated, except for during the process for the determination of independent variables. The credibility of these models remains untested since no effect of applying them are visible. (2) Models with evaluation processes lend themselves to statistical comparisons between simulated results and measured ones, by various metrics. The metrics were chosen arbitrarily in terms of statistics, without a comprehensive framework to judge whether a metric is appropriate to be used or not for the model evaluation. (3) The simulation and measured results were compared in a deterministic way, and there is no unified approach to evaluate the discrepancy between the two. To claim how large discrepancy implies a failure in the model evaluation is subjective in this context. Due to the stochasticity of occupant behavior models, the simulation results vary among multiple simulation runs, which requires a novel method to compare the two.

The validation methods vary, but there is one permanent principle: usefulness of a model should be assessed through its sustainability for a particular purpose [9,41]. Gaetani proposed a fit-for-purpose modeling strategy to emphasize the selection of model complexity and the model application, whose idea is that the model complexity and validity should be case specific according to the aim of the simulation [21]. Inspired by the strategy, this paper aims at proposing a scientific evaluation approach regarding stochastic occupant behavior models from an application-oriented perspective. As the fundamental viewpoint, the evaluation of the model should be oriented at its potential applications, thus corresponding metrics, implying that the application scenarios of the model are supposed to be specified prior to model evaluation. During the evaluation process, the stochasticity of occupant behavior models should be highlighted and statistical methods are to be referred to. For simplicity, the lighting behavior simulation is used as an example in building energy simulation at this very preliminary stage. To demonstrate the aforementioned concept, we take the lighting behavior models as an example.

1.3. Metrics for evaluation

The diversity of model application scenarios calls for distinct metrics in the model evaluation process. Application scenarios can be found in literature on lighting behavior modeling and relative fields, which the following text summarizes to provide potential metrics for the ensuing model evaluation.

1.3.1. Analysis on energy consumption and saving potential

The analysis on the induced energy consumption, as well as the energy saving potential, with the lighting behavior models involved, prevail in the current literature. Mahdavi [40] modeled lighting behavior in an office buildings, based on which the energy saving potential by alleviating the control strategy with automatic switch off and automated dimming regime. The significance of applying the two strategies could be observed from the simulation. Similar research was done, where various lighting control options, defined as constant, manual and automated in the paper, were simulated to conclude the resulting annual primary energy requirement [8]. The conclusion was in accordance with that drawn, that the manual control plus automated strategy performed best in terms of the energy consumption [40]. Other numerous studies on the lighting behavior modeling detailed discussions on the total energy consumption and energy saving potential in different contexts [32,33,37,42,51,66,69].

1.3.2. Typical profiles for energy simulation

The typical profile, considered as an average representation of the dynamic schedules differing from day to day, would suffice in cases where integrated dynamic simulation is required, which is a common approach to describe the lighting use schedules in current building simulation programs [68]. Eilers [17] obtained the daily occupancy profile during weekdays to have an overview on the relationship between occupancy patterns and lighting switch behavior. The results were interpreted to comment that people in the offices with occupancy sensors would rely on them to switch off the lighting, instead of switching it off manually. Chung and Burnett [15] proposed a model to simulate the occupancy and lighting state in the office building. Three events, namely the zone starting to be occupied, being temporarily unoccupied, and becoming vacant, were modeled for occupancy, while lighting was modeled as being on when the zone was occupied, and off after a variant delay when the zone was vacant. The profile for different delay time of lighting use were illustrated and compared to study the energy consumption.

1.3.3. Short-term demand prediction

The demand response with efficient power generation, transmission and consumption calls for the accurate short-term energy forecasting, thus the capability to well predict end users' behavior [11]. Stokes [55] proposed a novel approach to model sub-hourly domestic lighting demand, to facilitate investigations on urban electricity networks with solar technologies, where models with temporally high resolution are typically required to analyze the varying demand in the grid [53]. Richardson [50] presented a