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A Bayesian modeling approach of human interactions with shading and electric lighting systems in private offices

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ABSTRACT

In this paper, we present a hierarchical Bayesian approach to model human interactions with motorized roller shades and dimmable electric lights. At the top level of hierarchy, Bayesian multivariate binary-choice logit models predict the probability of shade raising/lowering actions as well as the actions to increase the level of electric light. At the bottom level, Bayesian regression models with built-in physical constraints estimate the magnitude of actions, and hence the corresponding operating states of shading and electric lighting systems. The models are based on a dataset from a field study conducted in private offices designed to facilitate a large number of participants and to collect data on environmental parameters as well as individual characteristics and human attributes governing human-shading and –electric lighting interactions. In this study, models were developed only for arrival periods due to the low frequency of actions during intermediate time intervals with continuous occupation. Our modeling framework demonstrates the advantages of the Bayesian approach that captures the epistemic uncertainty in the model parameters, which is important when dealing with small-sized datasets, a ubiquitous issue in human data collection in actual buildings; it also enables the incorporation of prior beliefs about the systems; and offers a systematic way to select amongst different models using the Bayes factor and the evidence for each model. Our findings reveal that besides environmental variables, human attributes are significant predictors of human interactions, and improve the predictive performance when incorporated as features in shading action models.

1. Introduction

Human-building interactions provide information on the energy impact of different control behaviors and are also used to infer occupant preferences and individual differences in experiencing thermal and visual environments; they reveal stimulus-response relationships for the integration of humans in sensing, control, and simulation frameworks. The focus of this paper is the study of human interactions with window shades and electric lights. Previous studies with similar focus, have been designed around two main objectives: First, to attain an understanding of the reasoning behind the human-building interactions towards the development of adaptive control algorithms [1–5]. Second, to develop stochastic models based on probabilistic relationships between human-shading and -electric lighting interactions and environmental conditions that represent the random nature of occupant behavior [6–9], and when used properly, achieve more reliable predictions in Building Performance Simulation (BPS) [10–14].

In this paper, we present a hierarchical Bayesian approach to model interdependent human interactions with motorized roller shades and dimmable electric lights, and to incorporate human attributes as features within the model structure improving its predictive performance. These systems are commonly implemented in office buildings, but there are only a few studies of human interactions [15,16], with no previous effort on model development. Our modeling framework is based on a field study in which occupants could manually operate shade and lighting systems or override an automatic controller; fully open or close events were possible as well as selection of intermediate positions of the shade and lighting system using wall-switches or web-enabled interfaces.

Section 2 presents background information on human interaction models for shade and lighting systems and outlines the research needs. Section 3 describes the field study while important observations relevant to the development of human-shading interaction models are presented in Section 4. The Bayesian mod-

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eling approach is described in Section 5 while model estimation results and their discussion are presented in Section 6. Section 7 briefly presents an algorithm for implementation of the developed models in building simulation. Conclusions and recommendations for future work are discussed in Section 8.

2. Background

This sections provides an overview of background information on stochastic modeling of human interactions with shading and electric lighting systems and outlines important advances and limitations that guided the methodology developed in this study.

2.1. Modeling approaches

Occupant-shading interaction models have been developed upon observational studies with duration that varies between five days to six years and present significant variation in the selection of variables as well as model formulation and structure. In some cases, observations include occupant-shading and electric lighting interactions [7,17] due to the obvious interdependency. Most studies consider that shades are fully deployed or fully retracted although partial opening/closing events are important [18] as daylight adequacy is not linearly related to shading position. The majority of the so-called stochastic models use input variables to predict the likelihood of a state change, e.g. blinds opening or closing action in the work by Haldi and Robinson [6]. With regards to the formulation, Bernoulli process [19], discrete-time Markov chain [20], and survival analysis [9,19,20] have been used previously. Recent studies [5,10,13,21,22] highlight general issues and limitations associated with the development of occupant behavior models in terms of their reliability and applicability, including the validation process and the generality of estimate parameters [10]. Also, data collection is often a costly process due to the amount of monitoring equipment and time required, while the selection of appropriate sample size for measurement duration, frequency, and the number of occupants remains an issue of debate. Generalized linear models such as logistic regression, which allow for non-normal distributions, are widely accepted for predicting probabilities of human-building interactions. To date, classical multivariate logit models along with maximum likelihood estimation have been developed to predict shading raising and lowering actions [6–8,23–25]. This typically results in point estimates of the parameters without consideration of epistemic uncertainty induced by the limited availability of data. A different approach, based on Bayesian paradigm automatically incorporates epistemic uncertainties in a natural way. Probabilistic uncertainty quantification (UQ) addresses decision-making problems in a principled manner [26]. Bayesian methods are useful in the sense that help us to combine existing knowledge (prior probability density distributions (PDFs)) with additional knowledge that is derived from the new data at hand (likelihood function). Bayes rule is used for combining prior knowledge with likelihood function, which results in the derivation of updated knowledge (posterior PDFs). These posterior PDFs can then be used as priors in subsequent analysis providing learning chains in science [27]. The standard deviation (SD) of the posterior distribution quantify the uncertainty about the sampling distribution and is also defined as standard error (SE). The study by Lindelöf and Morel [28] deployed the Bayesian formalism to infer the probability that any illuminance distribution should be considered by the user as visually uncomfortable. This was based on analysis of the past history of the user's interactions with the blind and lighting controls. However, Bayesian inference, despite of its advantages, has not been exploited in previously developed human-shading and lighting interaction models.

2.2. Model features

In previous studies, a wide range of indoor variables was monitored to investigate the triggers of occupant interactions with shading and electric lighting systems. These include indoor air temperature [29,30], work plane illuminance [31,29,6,23], average and maximum window luminance [7,30], vertical illuminance on VDU screens [31], daylight glare index and probability (DGP and DGI) [7], daylight work plane illuminance [32,33], solar penetration depth [24], and transmitted solar radiation [24,30,31]. Horizontal and vertical global illuminance and irradiance [29,31], outdoor temperature [23], solar altitude [23] are among the outdoor variables which were investigated. Seasonal effects [29], façade orientation [23,34], and sky conditions were considered as well. Rubin et al. [35] considered sunny, cloudy, and hazy conditions and found that blind position seemed to be independent of those. As a counter example, Rea [25] noticed that blind occlusion was significantly different between different sky conditions. This study also concluded that occupants have a long term perception of solar irradiances that may affect the use of blinds. Overall, findings [6,36] suggest that observed variations can be explained by variables such as solar radiation, daylight levels, and geometry. That is, considering local stimuli (indoor illuminances) offers promise for extension to other shading and building configurations as well as façade orientation [6]. However, some of the variables that have been reported to describe human-shading and – electric light interactions can be highly correlated (e.g. DGP and window luminance or solar penetration depth and indoor illuminances) and the selection of features is critical in order to avoid model inefficiency and overfitting.

The occupation dynamics was reported to be significant in the study by Haldi and Robinson [6] and different models were developed for the arrival and intermediate occupation period, supported by an extended dataset corresponding to a period of six years. This approach was adopted in subsequent studies [7] despite the significantly lower density of actions during the intermediate occupation period and the relatively small dataset on which the models were based. In this case, it is very likely for the model to treat the low number of actions as disturbances. That is, the model might still describe the general characteristics of the phenomenon, such as significant features and their directional attributes, but its predictive power might drop significantly.

Besides environmental variables, individual characteristics and human attributes, such as desire for view and connection to the outside have been reported as motives of occupant interactions with shading systems. Connection to outdoors directly relates to window shade design characteristics (color, openness factor) and position; it is an important aspect of visual environment [37,47] and previous studies have reported significant correlations between window view and glare perception [38,39]. However, window view, despite its significance, has not been used as model input to predict occupant interactions with shading systems. Visual privacy was also found to impact human-shading interactions [30,34] and Reinhart and Voss [17] attempted to correct the privacy-related bias in observations.

In an attempt to represent occupants' behavioral diversity, Haldi and Robinson [6] examined individual behaviors by estimating different regression parameters for all the 23 participants in the study. However, this approach only investigates variations among the observed occupants and does not provide generalized outcomes. That is, the reasoning behind the variations remains vague and related explanatory variables cannot be identified. Therefore, when applying the models to a new set of occupants in building simulation or control algorithms, it is required to randomly choose from observed behaviors, assuming transferability for individual differences. Instead, individual characteristics can be treated as model inputs in stochastic models of occupant behaviors, by deploying a